An investigation on the pay-off to generic competences for core employees in Catalan manufacturing firms

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ABSTRACT

The aim of this paper is to measure the returns to human capital. We use a unique data set consisting of matched employer-employee information. Data on individuals' human capital include a set of 26 competences that capture the utilization of workers' skills in a very detailed way. Thus, we can expand the concept of human capital and discuss the type of skills that are more productive in the workplace and, hence, generate a higher payoff for the workers. We also focus on the relationship between the returns to generic competences and traditional human measures of human capital and the content of the job. The rich information on firm's and workplace characteristics allows us to introduce a broad range of controls and to improve previous research in this field. This paper gives evidence that even after having controlled for a large set of variables, high-level communication and numeracy skills increase core employees' earnings. Our findings also signal that the returns to generic competences are much more related to the content of the job, rather than traditional human capital measures.

JEL Classification: J24, J31

1. Introduction

It is widely accepted that major changes occurred in the labour market in the recent years have deeply transformed workplaces. At the same time, a noticeable increase in earnings inequality has been reported, even within educational levels (Acemoglu, 2002). The spread of skill-biased technological change, the importance of human capital to be competitive, in addition to organizational changes have become central issues in this debate. In this sense, researchers have also turned their attention to the role that skills and competences have acquired in nowadays-jobs. For instance, Appelbaum (2000) reported that employers who raised the level of employees' involvement and skills achieved better outcomes. Part of these outcomes were transmitted to the employees in the form of higher earnings and satisfaction, although the gains were smaller in comparison with the employer. O'Shaughnessy *et al.* (2001) ascertained that the main increase in within-firm managers' earnings inequality can be attributed to rising returns to Hay points[1]. According to Heijke *et al.* (2003), human capital indicators such as tenure, grades, courses which have been traditionally used as a proxy for competences, do not longer suffice to predict career success properly. The interest for competences has led researchers to attempt to identify which are the most required ones, their degree of usage and their pay-off.

This paper aims to gain insight into the rewards to competences for core employees by introducing a suitable set of controls for individuals', firm and workplace specific characteristics. We focus on core employees of the manufacturing sector given that these workers have traditionally performed non-skilled and repetitive tasks associated to the fordist production system. Besides, the required level of human of human capital and their wages had been rather low. It is interesting hence, to evaluate to what extent competences have gained importance in this context, by analyzing how the utilization of these competences is rewarded by employers, to explore the link between competences and the traditional indicators of human capital, as well as other elements that depict the specific workplace and the degree of innovation of the firm. We ignore the existence of any other work that has strictly focused on returns to generic competences for core employees

[1] Hay points are described by O'Shaughnessy et al. (2001) as "an unusually good measure of job requirements and skills that can proxy for human capital". This measure is constructed by carrying out a detailed and consistent analysis of the skills required to perform a certain job.

A new and unique data set which contains wide information provided by workers and general managers of firms in the manufacturing sector makes it possible to meet our goals. Our approach follows previous works that examined the returns to generic competences by using surveys that deployed a job analysis methodology. The set of 26 competences builds on those works, and more specifically, it follows the work of Dickerson and Green (2004) which provided a highly informative description of workplaces and accurately estimated the value of 10 generic competences. Departing from the initial set of 26 competences, we derive measures of the utilization of a reduced structure of generic competences, evaluate the rewards to each of the latter, and shed some light on the relation between the returns to competences and the individuals' human capital, the content of the job, as well as innovation and organizational firm practices. Our specially designed matched employer-employee data set mitigates the impact of previously non-observed variables on the estimates of the pay-off to generic competences, and more specifically those related to firm characteristics, which had tended to be neglected. We are able to control for variables such as the ownership of the firm, the degree of internationalization, the level of technology and organizational firm practices.

The remainder of this paper is laid out as follows: next section covers main previous contributions in this field, in Section 3 we describe the survey data, in Section 4 we develop the model of generic competences, in Section 5 we estimate the returns to the generic competences, in Section 6 we isolate the R squared attributable to each of the generic competences by means of the Fields decomposition (Fields, 2003). In section 7, we decompose the earnings differential between "high-competence" workers and "low-competence" workers using different versions of the Oaxaca decomposition. Finally, in Section 8 main conclusions are presented.

2. Previous research

The number of contributions aiming to assess the rewards to competences is not abundant. Furthermore, there is no consensus on the competences that receive higher pay-offs. There are authors who advocate encouraging the acquisition of occupational specific competences (Bishop, 1995). Altonji (1995), Mane (1999), and Bishop and Mane (2004) found evidence of positive returns to vocational oriented course work. Alternatively, other researchers have highlighted the importance of academic competences such as mathematics (Murnane et al., 1995; Murnane and Levy, 1996; Tyler et al, 1999). Hanushek and Kim (1995) sustained that cognitive skills are

are an important determinant of labour productivity. More recently, Green *et al.* (2002) stated that numeracy and literacy skills are robust predictors of pay, results which are consistent with those obtained by McIntosh and Vignoles (2001) and Freeman and Schettkat (2001) regarding numeracy skills. Finally there is another group of contributions which focus on generic competences. Shapiro and Goertz (1998) showed that employers make their decisions on hirings not on the basis of academic knowledge, but on soft skills (motivation, attitude…).

In recent years, new available data sets derived from surveys based on job analysis have allowed the appraisal of the independent impact of generic competences on earnings. As a result, new evidence has emerged. Shadow prizes for each of the generic competences have been computed by means of hedonic wage equations. Green (1998) found that computer skills, professional communication and problem solving were highly valued competences. Also reading and writing short documents were important skills. On the other hand, client communication and numerical skills had little association with pay. Garcia Aracil *et al.* (2004) put forward that participative and methodological competences are best paid to university graduates. The evidence in Dickerson and Green (2004) signals that computer skills and high-level communication carry positive wage premia. Besides, it is also shown that the utilization of computing skills, literacy and numeracy skills, technical know-how, high-level communication skills, checking-skills and problem-solving grew in Britain between 1997 and 2001. Suleman and Paul (2007) concluded that cognitive and strategic competences yielded and increase of both fixed and variable earnings, whereas behaviour-towards-the-organization competences only raised variable earnings and general knowledge only raised fixed earnings.

Assessing the returns to human capital competences has become a matter of special interest, given that it provides an insight into the competences that need to be promoted. However, it is not an easy task. Earnings are determined by a large set of variables, some of which are unobservable. Abowd *et al.* (1999b) found that individual non-observable characteristics are an important source of wage variation in France. Firm heterogeneity was as well found to be a major source of wage variation, although its influence was more modest. Abowd et al. (2004) suggested that both individual and firm wage effects reflected person-specific and firm-specific productivity due to unobserved characteristics. Thus, despite recent efforts to build frameworks that reflect the competence structure of each workplace, rewards to the competences can be flawed if models do not properly control for the individual and firm context in which the job takes place. Overcoming the effects of unobserved heterogeneity is possible by controlling for time-invariant heterogeneity (Corneliβen and Hübler, 2007). Another option is to access to richer data sets that enable researchers to control for previously unobserved characteristics. When the target is to measure the returns to competences, given the difficulties to conduct adequate panel surveys, especially in terms of time and money constraints, the best option appears to be the diminution of biases arisen from the effect of individual and firm heterogeneity by including better controls for firm and individual characteristics in cross-sectional data sets.

3. Data

3.1 The Survey

The data set used in this paper derives from a specially designed survey for an ambitious research project which pursues an in-depth analysis of Catalan small-and-medium-size firms from different levels of analysis: workers' level, firm level and geographical level. Firms participating in the project belonged to 6 different manufacturing sectors and to 3 sectors of the service industry and agreed to collaborate with the project during 2005 and 2006. Questionnaires were responded in a stratified manner by samples of workers chosen to mirror the real structure of the firms[2]. Four types of questionnaires were delivered, depending on the position in the firm: general manager, managers, supervisors and core employees. The questionnaires distributed among general managers asked for wide information on the main characteristics of the firm (size, ownership, degree of internationalization), evolution and position in the market in which the firm operates, production technology, product strategy, characteristics of the most important product, organizational practices and workers' management. The questionnaires handled to the core employees consisted of a detailed investigation of the nature of the workplace. Questions ranged from human capital and other specific characteristic of the worker, to a comprehensive description of the workplace, both in contractual terms (working hours, earnings, type of contract…) and in terms of what the job entailed (competences required, required time to reach the optimum level of productivity in the job, degree of intensity, degree of freedom to organize tasks).

[2] Thus the sample is representative of both firm sizes, in terms of the number of workers, and the hierarchy of professional categories within firms.

3.2 Descriptive statistics

The initial sample comprises 4863 workers in 502 firms. If the sample is restricted to core employees working in manufacturing firms, 2516 workers in 320 firms are kept. Because of missing values, the final sample contains 2088 observations that are related to 311 firms[3].

Table I in the Appendix contains the main descriptive statistics. 69% of the respondents report being within the 2ond and 3rd interval, that means perceiving between 700€ and 1300€ per month[4]. The sample is basically composed by men, reflecting men predominance in manufacturing sectors. The level of education is low, since an 18%, still a large percentage, has received no education certificate, and a further 32% has barely completed compulsory education. A 37% has completed some form of vocational educational. Tertiary education represents a 5% of the sample. Despite the low level of education, an 80% reports some type of overeducation. The majority of the respondents have a permanent contract (90%) and work between 35 and 40 hours per week (84%). The sectors studied are the food industry, electronics, rubber and plastic materials, metal products and furniture and other manufacturing. More than half of the core employees work in firms located in the Metropolitan Area of Barcelona. Firms participating in the survey are small- and medium-sized firms. 60% of the core employees of the sample worked in firms ranging from 10 to 50 workers. 81% of the firms can be considered familiar firms, and in more than a third, the ownership coincides with management. The level of internationalization is relatively low, both in terms of foreign participation in the firm and foreign sells. The table shows that some technologies are more spread than others. For instance, the internal net of data exchange is present in 73% of the observations. Similarly, some organizational practices are much more spread than others. Systems for sharing information between workers and managers and job rotation are the most common practices. Regarding product innovation, in the 74% of the observations, some kind of product innovation has taken place in the previous 2 years.

4. Analysis of the competences

[3] Given the large number of missing values in the variables that capture organizational practices, production technology and product innovation (between 10% and 15% in each of the cases), we have decided to generate dummy variables that take value equal to 1 when there is no answer to the question. Not having to drop these variables, we reduce the likelihood of selection problems.

[4] The level of earnings is referred to a usual month net payment, hence excluding special temporary circumstances. However, it includes both the fixed component and the variable component of earnings.

4.1 Generic Competences for core-employees in the manufacturing sector

Core employees had to examine to what extent their jobs involved a set of 26 competences, which are shown in table II in the Appendix. Respondents were asked to evaluate the importance of each competence. The scale of possible answers included "not important at all", "not very important", "fairly important", "very important" and "essential". The 26 competences needed to be reduced into a more easy to interpret set of generic competences. Factor analysis is used with this object. Factor analysis is a well known technique that allows a simplification of a large set of initial variables into a much reduced set of factors, which function as linear combinations of the original variables. Besides, these factors can be used as indexes that evaluate the situation of a certain group of individuals in relation to the mean. In order words, the factors can be used to measure to what extent certain groups utilize generic competences.

The first step is to change the ordinal scale of the 26 initial competences to a cardinal scale, ranging from 1 "not important at all" to 5, "essential". Factor analysis is then applied, although it is necessary to rotate the factors obtained in order to aid interpretation. An orthogonal rotation[5] has been applied to the data. Table 1 presents the factors loadings that depict the strength of the relationships between each of the initial competences and the factors generated. The number of retained factors is contingent on the subjective criteria of the researcher, although there are some rules that are recommended to follow. According to eigenvalues (they should be larger than 1), after a preliminary Principal Components Analysis, we should have kept 5 factors and have rejected the others. Following this rule, the percentage of variance explained by the factors would have reached 65%. Nonetheless, the eigenvalue of the 6th factors is above 0.96, the eigenvalue of the 7th factor is 0.89, and the eigenvalue of the 8th factor is 0.72. Once these 3 additional factors are considered, the percentage of explained variance increases to 75%, which is more than acceptable.

[5] Notwithstanding the fact that an oblique rotation would have shown the correlations between the generic competences, the high correlations emerging between them make the orthogonal more advisable.

Table 1. Factor loadings after orthogonal rotation

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Uniqueness
Dealing with people	0.1360	0.3832	0.2508	0.1866	**0.4047**	0.0423	0.0711	0.0386	0.5648
Selling	0.0619	**0.8096**	0.1259	0.1424	0.1081	0.0953	0.0642	-0.0245	0.2791
Advising	0.1177	**0.8120**	0.1487	0.1536	0.0878	0.1352	0.1390	0.0515	0.2332
Presentations	0.0965	**0.6630**	0.0821	0.2557	0.0787	0.1493	0.0955	0.2688	0.3692
Persuading	0.1081	0.3804	0.1261	**0.4674**	0.1471	0.0641	0.1150	0.1425	0.5500
Planning others	0.1596	0.2392	0.1852	**0.6967**	0.1282	0.1092	0.1093	0.0580	0.3539
Delegating	0.1958	0.3243	0.2382	**0.6624**	0.1389	0.1340	0.0639	0.0583	0.3162
Planning ownself	0.2425	0.1880	**0.7025**	0.2623	0.1235	0.1205	0.1132	0.0276	0.3002
Organizing own time	0.2585	0.1508	**0.7356**	0.1347	0.1818	0.0893	0.0947	0.0338	0.3000
Thinking ahead	0.3395	0.2323	**0.4782**	0.1101	0.3546	0.1450	0.0636	0.1288	0.4226
Learning continuosly	0.3964	0.1832	0.3636	0.0717	**0.4836**	0.1826	0.1007	0.0738	0.3892
Working with people	0.2847	0.1497	0.2208	0.2124	**0.6122**	0.0547	0.1224	0.0273	0.4091
Listening	0.3367	0.1208	0.1857	0.1581	**0.6186**	0.0795	0.1231	0.0721	0.4032
Teaching	0.3530	0.2816	0.1689	**0.4106**	0.3603	0.1429	0.0431	0.0793	0.4406
Reading short	0.1961	0.2969	0.1497	0.1955	0.1767	0.2922	0.1965	**0.4469**	0.4578
Reading long	0.1594	0.3191	0.0802	0.2195	0.1015	0.3673	0.2349	**0.4439**	0.4207
Simple calculations	0.2609	0.1383	0.1292	0.0767	0.0751	**0.6819**	0.1510	0.0271	0.3960
Complex calculations	0.2391	0.2177	0.1176	0.1479	0.0725	**0.6907**	0.1130	0.1122	0.3520
Spotting problems	**0.7727**	0.0610	0.1151	0.1082	0.1368	0.1781	0.0876	0.0091	0.3160
Cause of problems	**0.7561**	0.1229	0.1601	0.1852	0.0794	0.1565	0.1362	0.0904	0.2958
Solution to problems	**0.7670**	0.1554	0.2105	0.1463	0.1399	0.1623	0.0945	0.0673	0.2624
Noticing mistakes	**0.8191**	0.0449	0.1183	0.0584	0.1174	0.0555	0.0773	0.0241	0.2862
Detail	**0.6646**	0.0330	0.1336	-0.0003	0.2302	0.0718	0.1225	0.0236	0.4657
Computer	0.1893	0.2241	0.1215	0.0956	0.0905	0.3532	**0.4197**	0.1446	0.5600
Knowledge of products	0.2881	0.2620	0.1636	0.1392	0.1408	0.1673	**0.5968**	0.0564	0.3951
Specialist knowledge	0.3347	0.1924	0.1657	0.1192	0.1545	0.2590	**0.5543**	0.1188	0.3971
Taxonomy of the generic competences	**Problem solving**	**Client Communication**	**Planning skills**	**High-level communication**	**Horizontal communication**	**Numeracy skills**	**Technical know-how**	**Literacy skills**	
Standard deviation	0.9225	0.8916	0.8352	0.7972	0.8189	0.8026	0.7404	0.6355	
Cronbach's Alpha	0.9052	0.8678	0.8291	0.8263	0.8063	0.8094	0.7744	0.7505	

Notes: Orthogonal rotation has been carried out and the regression method has been chosen to derive the factors.
Factors loadings larger than 0.4 appear in bold.
None of the standard deviations are equal to one. This is purely a theoretical result, only achievable if the original variables are perfect linear combinations of the factors.
Cronbach's Alpha measures internal consistency of the factors by considering inter-item correlation.

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Table 1 shows the factor loadings emerging after having retained 8 factors. Three additional methodological reasons prompted us to finally retain 8 factors. First, uniqueness values were acceptably low[6]. Second, the internal consistency of the factors measured by the Cronbach's Alphas was rather high[7]. And finally, each variable appears related at most to one factor (figures in bold in Table 1)[8]. Thus, the principle of simplicity put forward by Thurstone (1947) is fulfilled and a readily straight forward classification of competences can be established. This simplicity made easier the selection of the taxonomy. Although it entails a certain part of subjectivity, it is primarily the consequence of common sense applied to the data.

The 8 generic competences emerging from factor analysis are: problem-solving, client communication, planning skills, high-level communication, horizontal communication, numeracy skills, technical know-how and literacy skills. This structure is mainly consistent with the results obtained by Dickerson and Green (2004), with the difference that they had a further category, they called checking skills, which appears in Table 1 as a part of problem solving. They also took computer skills as an independent category, whereas in our case they fit reasonably well within the technical know-how. Generating the factors is the last step of the procedure, for which, the regression technique was used[9].

4.2 Situation of certain groups

By construction, factors are indexes with mean equal to 0, and a theoretical standard deviation equal to 1. This fact allows researchers to examine the situation of certain groups in relation to the factor mean. Table 2 depicts the situation by gender and the highest level of education attained. By gender, a distinct pattern of competences emerges. That is, men are more involved in problem-solving, planning, high-level communication, and numeracy activities. Alternatively, women activities are more related to client communication, horizontal communication, technical know-how, and literacy skills. The table also reveals that, as expected, the higher the level of education

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[6] Uniqueness values denote the residual part of original variables that cannot be explained by the factors. It is widely accepted that above the threshold of 0.7, uniqueness values start to cause concern. As it can be noticed, only 3 of the uniqueness values exceed 0.5, and none of them reaches 0.6.

[7] Literature considers as acceptable Alphas larger than 0.7. All the Alphas computed exceeded that threshold. In fact, only the 7th and the 8th Alpha were lower than 0.8.

[8] Those factor loadings larger than 0.4 are shown in bold.

[9] Regression-scored factors have the smallest mean squared error from the true factors. The major inconvenient of this technique is that it can give rise to biased factors. On the other hand, factors generated following the methodology suggested by Barlett overcome possible bias problems, although they may be far less accurate.

attained, the higher deployment of competences. Some of the factors follow an almost perfect monotonical increasing trend (numeracy, technical know-how, and literacy). However, there are some remarkable features that should be highlighted. Problem-solving seems reserved for compulsory and vocational education. Surprisingly, besides individuals with compulsory or basic vocational educational, only 4-year university graduates are required above average high-level communication competences.

Table 2: Mean levels of generic competences by gender and highest education level attained

	Male	Female	No qualif.	Comp.	Voc. 1	Sec.	Voc. 2	Voc. 3	3 degree	4 degree	PhD
Obs.	1574	514	366	670	346	170	340	78	90	25	3
Prob. solv.	0.034	-0.104	-0.129	0.030	0.026	-0.040	0.091	0.211	-0.227	-0.136	0.546
Client com.	-0.027	0.084	0.124	-0.069	-0.059	0.035	-0.032	0.110	0.129	0.189	0.502
Planning	0.006	-0.018	-0.067	-0.032	0.114	-0.035	0.023	-0.196	0.150	0.286	-0.170
High com.	0.053	-0.161	0.018	0.011	0.068	-0.039	-0.037	-0.192	-0.155	0.327	0.717
Horiz. com.	-0.008	0.025	0.048	-0.014	-0.017	0.009	-0.031	0.005	0.063	-0.006	0.164
Numeracy	0.037	-0.113	-0.105	-0.059	-0.008	0.096	0.050	0.136	0.317	0.352	-0.159
Tec. know.	-0.013	0.039	-0.238	-0.113	-0.039	0.207	0.158	0.378	0.530	0.316	0.747
Literacy	-0.004	0.014	0.014	-0.037	-0.045	-0.061	0.003	0.099	0.293	0.348	0.748

Abbreviations: Problem-solving (Prob. solv.), Client communication (Client com.), High-level communication (High com.), Horizontal communication (Horiz. com.), Technical know-how (Tec. know.); No qualify. (No qualifications), Basic Vocational Education (Voc. 1), Secondary Education (Sec.), Medium Vocational Education (Voc. 2), Higher Vocational Education (Voc. 3), 3-year-degree (3 degree), 4-year-degree (4 degree).

The data set allows checking the link between the utilization of competences and other variables. Table 3 explores how competences are related to other dimensions of the job, such as the degree of intensity and the time core employees need to reach the optimal level of productivity. The level of utilization of competences turns up to be monotonically increasing with both the time needed to be productive at job, and the degree of intensity, being trends much clear in comparison with the highest level of education attained[10]. In other words, the use of competences appears to be more related to the specific context of the job, rather than individuals' human capital. This first conclusion underpins the position of those who regard that traditional measures of human capital are not sufficient to predict labour market outcomes[11].

[10] There are some exceptions nevertheless. Jobs involving a maximum level of client communication competences, specific know-how, and literacy skills require a period between half year and a whole year so that workers reach the optimal degree of productivity.

[11] Although not shown in the paper, other forms of human capital have been also considered. The relation between the use of competences and experience presents an inverted U-shape, consistent with the change in working environments in which, older workers would have not taken part. A conclusive relationship with tenure does not turn up. Finally, workers who have some sort of training need more competences at their jobs when compared with workers who are not provided any sort of training. However, differences in table 4 are much larger.

Table 3: Mean levels of generic competences by job characteristics											
	Time needed to reach the optimal level of productivity						Degree of agreement with the statement: my job requires my working intensively				
	< 1 Month	1-3 months	3-6 months	1/2-1 year	1-2 years	> 2 years	Strongly disagree	Disagree	Neither	Agree	Strongly agree
Obs.	243	465	367	375	345	293	31	87	590	889	**491**
Prob. solv.	-0.256	-0.100	-0.043	0.112	0.104	0.159	-0.521	-0.356	-0.111	-0.014	0.254
Client com.	0.016	-0.058	-0.014	0.037	0.034	0.010	-0.066	0.019	-0.035	0.014	0.018
Planning	-0.151	-0.108	0.021	0.026	0.041	0.190	-0.201	-0.205	-0.101	0.014	0.145
High com.	-0.034	-0.012	-0.067	0.033	0.027	0.056	-0.444	-0.018	-0.154	0.004	0.208
Horiz. com.	-0.197	-0.091	-0.006	-0.010	0.130	0.175	-0.150	-0.031	-0.070	-0.006	0.111
Numeracy	-0.259	-0.165	0.009	0.026	0.104	0.308	-0.337	-0.090	-0.046	0.016	0.063
Tec. know.	-0.209	-0.061	0.124	0.083	0.023	-0.019	-0.150	-0.170	-0.071	0.033	0.066
Literacy	-0.006	-0.034	0.020	0.065	0.028	-0.083	-0.146	0.009	-0.033	0.015	0.020

Abbreviations: Problem-solving (Prob. solv.), Client communication (Client com.), High-level communication (High com.), Horizontal communication (Horiz. com.), Technical know-how (Tec. know.).

5. The returns to competences

The most common strategy to determine the value of generic competences has been the estimation of hedonic wage equations where log wages are the dependent variable. Mincerian wage equations are augmented with job attributes, which are considered characteristics of the job that must be to some extent compensated. Therefore, their coefficients are regarded as their shadow prices. The model we estimate is presented in equation (1):

$$\ln W_i = \alpha + Comp_i \beta + Ind_i \delta + Firm_i \phi + HC_i \varphi + Job_i \gamma + Innov_i \eta + \upsilon_i \qquad (1)$$

Where, the dependent variable ($\ln W_i$) is the logarithm of earnings, the set of eight generic competences is represented by the matrix $Comp_i$, Ind denotes individuals' control variables save human capital, $Firm_i$ contains both characteristics of the firm and the contract, HC_i comprises individuals' human capital, Job_i captures the content of the workplace in detail, and finally, $Innov_i$ includes a set of dummy variables that ascertain whether the firm deploys certain organizational practices, production technologies or whether the firm has carried out some sort of product innovation in the 2 preceding years. υ_i denotes the error term of the model[12]. The inclusion of these variables in the model is justified on the basis of findings that signal large effects of non-observed individuals' and firms' characteristics. Unless these effects are somehow considered, the estimates may suffer from significant biases. The inclusion of these controls would allow a closer approach to the real pay-off of generic competences. We were especially concerned about this issue, since

[12] Detailed descriptive statistics of the independent variables of the model can be found in the Appendix.

previous research has found evidence of a large effect of individual heterogeneity on wages (Abowd *et al.*, 1999b). Moreover traditional observable measures of human capital have been proved not to properly capture it. Fortunately, the data set includes valuable information to mitigate biases. Actually, generic competences by themselves are an indicator of individual unobserved ability. Furthermore, the presence of problems of overeducation is often related with less skilled individuals (Bauer, 2002; Chevalier 2003). Finally, the characteristics of the workplace are also an indirect measure of the ability of the person who works in it, specially the required time to reach the optimal level of productivity. It must be said that these considerations are made in the grounds of the correct match between the ability of the individual and the job nonetheless[13]. Better than usual controls for firm characteristics are also introduced, given the existing evidence of the impact of firm characteristics on wages[14].

The estimation of the model would be readily straight forward if we did not take into account the categorical nature of the dependent variable. Although we can observe the upper and the lower limits of each interval – with the exceptions of the lower limit of the lowest interval and the upper limit of the highest interval – the exact amount of earnings is unknown. According to Stewart (1983) ad-hoc OLS estimation entailing assigning each interval its mid point generally leads to inconsistent estimators. He suggested that it is possible to obtain better estimators by assuming a distribution for the continuous although unobserved dependent variable and estimate the model by Maximum Likelihood. We assume that our earnings variable is log-normally distributed[15]. The estimator is in fact a generalization of the Tobit model.

Table 4 presents the results of the returns to competences for different estimated versions of equation (1) depending on the variables included and excluded. Model 1 estimates the rewards to the generic competences

[13] The existence of matching problems would undoubtedly impinge on the quality of these controls. The rigidity of the Spanish labour market, negative attitudes towards job mobility, as well as constraints to promotion and demotion can distort these measures of individual ability.

[14] Groshen (1991) found that a non negligible part of wage variation was due to firm effects. Her results gave rise to a stream of literature which obtained similar results (Mizala and Romaguera, 1998; O'Shaughnessy *et al.*, 2001, Simón, 2005; Lane *et al.* 2007). The approach used by this strand of contributions has been criticized because firm effects are contaminated by non-observed individual heterogeneity. However, once time-invariant heterogeneity is considered, it is found that firm (both in terms of observable and non-observable characteristics) still remains an important determinant of wages (Abowd et al., 1999b). According to Abowd *et al.* (1999a), firm unobserved heterogeneity accounted for 24% of wage variance using data provided by the State of Washington Unemployment Insurance System.

[15] This seems a reasonable assumption, except for the highest interval, in which a Pareto distribution seems more plausible.

without taking into account any of the control variables. The utilization of five of the competences generates a positive and significant pay-off. These are problem-solving skills, planning skills, technical know-how, high-level communication and numeracy skills. The returns to the latter two generic competences are considerably higher with respect to the other. Conversely and surprisingly, horizontal communication appears to be negatively compensated. No significant pay-off emerges from literacy skills and client communication. Once controlling for contractual conditions in addition to individual and firm characteristics, in model 2, returns to client communication turns positive and significant, whilst the problem-solving coefficient is no longer significant. Pay-off to high-level communication and numeracy skills dwindle sensibly, although they keep being the highest ones. These coefficients are more than halved in model 3 (with respect to model 1). The introduction of human capital makes the coefficient on technical know-how no longer significant. Thus, the utilization of technical know-how is highly related to the traditional indicators of human capital. In model 4, instead of human capital, the characteristics of the workplace are introduced. As a result, both the positive and significant effects of client communication and planning skills vanish. At the same time, the positive impacts of numeracy skills and high-level communication on earnings notoriously diminish. Thus, these four generic competences are much more related to the workplace environment rather than human capital measures. The inclusion of the innovation behaviour of the firm (model 5) does not produce remarkable changes, with the exception of client communication, which again loses significance. In sum, there are two generic competences – high-level communication along with numeracy skills – that produce consistent and positive pay-offs, even after adding the series of control variables into the specification. According to the estimates of the full model (model 8), a one-standard-deviation increase in the utilization of these generic skills results in a pay rise of 1.1% and 1% respectively[16]. The evidence obtained by Dickerson and Green (2004) is consistent with the positive returns to high-level communication, although not in the dimension of the effect (theirs was around 8%). The difference in the coefficient can attributed in part to the fact that our analysis is centred on core employees and our list of control variables is more complete. By contrast, they found negative or non significant returns to numeracy skills. The positive rewards to numeracy skills are nevertheless consistent with other previous works (McIntosh and Vignoles, 2001; Freeman and Schettkat, 2001). The fact that the significant effect of client communication and planning skills vanishes with the inclusion of

[16] These increases are calculated as exp(0.014 X 0.7972) – 1 = 1.12% for high-level communication and exp(0.0126 X 0.8026) – 1 = 1.02% for numeracy skills. 0.7972 and 0.8026 are respectively the real standard deviations of each of the variables.

workplace variables is a sign that these variables are much related to the job environment, whereas technical know-how appears to be more linked to the more traditional measures of human capital. The consistent negative pay for jobs involving horizontal communication arises as a puzzle. It could be considered that the utilization of these skills makes the worker less productive performing their own activities, or simply, managers may not appreciate these skills.

Although not included in Table 4, it is worth commenting the estimates of the pay-off for the wide list of control variables, which broadly speaking are in accordance with prior results reported in the literature: lower returns for women, immigrants, and individuals with temporary contracts. Contrary to our expectations, variable earnings are not associated to higher pay. The positive firm size effect and the proportion of exports become non significant after introducing production technology, product innovation and organizational practices. Working in a firm which is part of a group yields higher pay. The strong effects of human capital variables simply echo previous findings and support the view that they are still an important determinant of wages. However, we must highlight the premium related to the time required to reach the optimal level of productivity. This measure of the complexity of the job carries a remarkable wage premium. Freedom to organize own tasks is also compensated. Neither product innovation, nor most of the organizational practices, nor most of production technologies are linked to higher earnings[17]. In some cases, they are even associated with lower wages (jobs in firms deploying systems for sharing information between managers and core employees, quality circles, and flexible production systems) [18]. Only job rotation and artificial sight control systems are connected with higher wages. These results are not completely at odds with prior studies. Doms *et al.* (1997) document that the premium for workers using more sophisticated capital drops after introducing individual characteristics in the specification. Osterman (2006), in spite of finding a robust positive pay-off for core blue collar employees involved in High-Performance-Work-Organization, recognizes the lack of consistency of previous research, which fell in several contradictions.

[17] Dummy variables that denote missing observations within the innovation variables have been included.

[18] We have also considered specifications with count variables (ranging from 0 to 8) regarding organizational practices and production technology. None of them was significant.

Table 4. Returns to Generic competences. Hedonic wage equations

	MODEL 1 Only competences		MODEL 2 Individual, firm and contract characteristics		MODEL 3 Human capital is added		MODEL 4 Job characteristics are added		MODEL 5 Innovation is added		MODEL 6 Full model	
Problem-solving	0.0169***	(0.0062)	0.0009	(0.0052)	0.001	(0.0051)	-0.0097*	(0.0054)	0.0034	(0.0053)	-0.0056	(0.0053)
Client communication	-0.0087	(0.0069)	0.0106*	(0.0062)	0.0119**	(0.0058)	0.0035	(0.006)	0.0106	(0.0065)	0.0075	(0.0059)
Planning skills	0.0185**	(0.0074)	0.0237***	(0.0061)	0.0195***	(0.0056)	0.0081	(0.0063)	0.0223***	(0.0061)	0.0066	(0.0061)
Horizontal communication	-0.0147*	(0.0079)	-0.0133*	(0.0069)	-0.0111*	(0.0065)	-0.018***	(0.0067)	-0.0151**	(0.0068)	-0.0158**	(0.0062)
High-level communication	0.0502***	(0.0077)	0.0274***	(0.007)	0.0214***	(0.0067)	0.0179***	(0.0068)	0.0269***	(0.007)	0.014**	(0.0065)
Numeracy skills	0.0486***	(0.0079)	0.0315***	(0.0071)	0.024***	(0.0067)	0.016**	(0.0069)	0.0285***	(0.0071)	0.0124*	(0.0066)
Technical know-how	0.0151*	(0.0085)	0.0201***	(0.0071)	0.0036	(0.0071)	0.0132*	(0.0069)	0.0189***	(0.0072)	0.0005	(0.0069)
Literacy skills	-0.0023	(0.0099)	0.0013	(0.0085)	-0.0049	(0.008)	0.005	(0.0082)	0.0037	(0.0086)	0.0005	(0.0079)
St. error of est. / Log likelihood	0.2629	-3015.88	0.2181	-2644.57	0.2015	-2502.06	0.2086	-2563.37	0.2138	-2607.99	0.1935	-2429.44
Chi² / Probability	117.23	0.00	1006.02	0.00	1460.55	0.00	1373.65	0.00	1246.81	0.00	1881.28	0.00
Control for missing innovation var.	NO		NO		NO		NO		YES		YES	
Sector dummy variables	NO		YES		YES		YES		YES		YES	
Regional dummy variables	NO		YES		YES		YES		YES		YES	

N = 2088

Robust standard errors in parentheses; * denotes significant at 10%; ** denotes significant at 5%; *** denotes significant at 1%

Referential variables appear in Table I of the Appendix.

Individual characteristics are gender, nationality and whether the individual is handicapped.

Contract characteristics are whether the contract is temporary, hours of work, whether the worker receives incentive pay and overtime pay.

Firm characteristics are number of workers, whether it is part of a group, whether is family-owned, whether is participated by foreign investment, whether the owner is also the general manager, and percentage of foreign sales.

Human capital measures are maximum level of education attained, tenure, whether the individual receives job training, experience, overeducation and undereducation

Job characteristics are the required time to reach the optimal level of productivity, intensity in the job, degree of freedom to organize own tasks and how easy it would be find a similar job.

Innovation variables are dummy variables denoting organizational practices (Worker suggestion program; Systems for sharing information between managers and core employees; Job rotation; Workplace redesign; Problem-solving teams; Semiautonomous teams of work; Quality Circles; Total Quality Management); production technology dummy variables (Automatic sensors for controlling inputs and outputs; Warehouse managementautomatic systems ; Flexible production system; Artificial sight control systems; Quality control automatic systems; Assisted productions by means of robotic elements; Data exchange internal network; Computer-assisted engineering systems) and product innovation.

See Table I in the Appendix for a detailed description

6. Competences and earnings differentials.

In the precedent section, it has been shown that both high-level communication and numeracy skills are important determinants of core employees' pay, even after controlling for human capital and job characteristics. At this point, it is interesting to assess to what extent generic competences account for earnings differentials. We use Fields decomposition which is a technique devised by Fields (2003) allowing researchers to linearly decompose log earnings differentials.

The total variance of our dependent variable can be expressed as:

$$\sigma^2_{w_i} = \sum_{k=1}^{K} \sigma_{\beta_k X_{ki}, w_i} + \sigma_{\varepsilon_i, w_i} \quad (2)$$

Where, $\sigma_{\beta_k X_{ki}, w_i}$ denotes the covariance between log earnings and each of the k independent variables, and $\sigma_{\varepsilon_i, w_i}$ represents the covariance between log earnings and the error term. As a result of dividing both sides of the identity by $\sigma^2_{w_i}$, the left-hand side becomes equal to 1, while the right-hand side turns into the sum of the proportions of the total variance that each of the explanatory variables and the error term account for.

$$1 = (\sum_{k=1}^{K} \sigma_{\beta_k X_{ki}, w_i} + \sigma_{\varepsilon_i, w_i}) / \sigma^2_{w_i} = \sum_{k=1}^{K} S_k + \sigma_{\varepsilon_i, w_i} \quad (3)$$

The contribution of each of the variables to the total variance can be easily calculated, as presented in (4). The sum of the K contributions (excluding the error term) is equal to the non-adjusted R squared.

$$S_k = (\sigma_{\beta_k X_{ki}, w_i} / \sigma^2_{w_i}) = (\beta_k \sigma_{X_{ki}} \rho_{X_{ki}, w_i}) / \sigma_{w_i} \quad (4)$$

The estimation technique in the previous section was not linear. This prompts us to regress, using OLS, the expected values of log earnings, conditional on falling within their intervals, against the set of explanatory variables included in the models of section 5[19]. Table 5 presents the results of the decomposition indicating the percentage of the total variance that each of the generic competences accounts for in each of the models.

[19] Obviously, knowing the exact pay would be the most desirable option. Given that it is not possible, we prefer to use the expected values of log earnings from interval regressions from section 5, rather than mid points of the intervals.

Table 5. Fields decomposition. Percentage of the total variance explained by generic competences						
	MODEL 1 Only competences	**MODEL 2 Individual, firm and contract characteristics**	**MODEL 3 Human capital is added**	**MODEL 4 Job characteristics are added**	**MODEL 5 Innovation is added**	**MODEL 6 Full model**
Problem-solving	0.0071	0.0002	0.0003	-0.0034	0.0012	-0.0019
Client communication	-0.0001	0.0000	0.0001	0.0000	0.0000	0.0000
Planning skills	0.0071	0.0073	0.0061	0.0025	0.0068	0.0021
High-level communication	0.0382	0.0175	0.0131	0.0109	0.0167	0.0080
Horizontal communication	0.0018	0.0013	0.0011	0.0018	0.0015	0.0015
Numeracy	0.0389	0.0216	0.0164	0.0111	0.0196	0.0088
Technical know-how	0.0045	0.0047	0.0007	0.0030	0.0045	0.0000
Literacy	-0.0003	0.0001	-0.0006	0.0005	0.0004	0.0001
All generic competences	0.0973	0.0527	0.0371	0.0265	0.0505	0.0186
Unadjusted R-squared	0.0973	0.534	0.6336	0.5935	0.5611	0.6862

N=2088 observations

Note: These percentages are derived from OLS regressions. Continuous log earnings estimated as the expected value of log earnings conditional on falling in the correct interval.

The first column (model 1) shows that a regression that solely includes the generic competences as explanatory variables achieves a non-adjusted R squared near to 10%[20]. The percentage of variance that competences account for is almost halved once individuals' and firm characteristics besides the contractual terms are considered (model 2). High-level communication and numeracy skills can independently still account for around 2% of the total log earnings differentials nonetheless. None of the other competences can explain more than 1% of the variance, although planning skills account for a 0.7% and technical know-how a percentage close to 0.5%. Both the inclusion of human capital (model 3) and job characteristics (model 4) produces considerable drops of the percentages, whereas the introduction (model 5) of innovation variables practically does not make any difference. According to the figures in the table, it is undeniable that the effect of generic competences appears to be more related to the content of the job rather than to traditional human capital measures. This does not exclude that the percentage accounted for by technical know-how plummets once human capital is taken into account. On the other hand, pay-offs to high-level communication, numeracy skills and planning skills are much more associated with the content of the job. It should be noted that the unadjusted R-squared of model 3 is larger when compared with model 4, highlighting the still higher predicting capacity of human capital measures.

The results emerging from Model 6 signal that earnings inequality among core employees within manufacturing firms due to generic competences visibly fall when all variables are considered. In fact, less than 2% of earnings differentials are explained by the effect of generic competences. This should not be interpreted as generic

[20] Since no other variables are included, the sum of the proportions explained by the generic competences is equal to the non-adjusted R squared.

competences being of little account. In fact, this result is principally informative of the fact that rewards to generic competences are in part captured by the pay-off to human capital measures, and more particularly by the pay-off to job characteristics. The remaining percentage is basically composed by the effects of high-level communication and numeracy skills, which still explain 0.8% and 0.88% of log earnings variance respectively.

7. The wage gap between high-competence and low-competence core employees

We have already provided evidence that the utilization of some generic competences is rewarded for core employees, and at the same time, that higher pay to generic competences can be in part explained by human capital and the job context. At this stage, we aim to explore the sources of earnings gap between those core employees whose job involves a high degree of utilization of generic competences and those core employees whose job do not require a high level of utilization of generic competences. The first step is to construct an index of utilization. A diversity of criteria can be devised. We have opted for a linear combination of the factors using the percentage of explained variance of the initial 26 competences as it seemed a reasonably objective measure[21]. By construction, the mean of this index equals 0[22]. Core employees can be divided in 2 main groups depending on whether their utilization of generic competences is above average (the new variable will take positive values), or alternatively, their utilization of generic competences is below average (the new variable will take negative values). As a result of this classification, we derive an additional indicator variable which is equal to 1 if the core employee uses competences above average (high users), and is equal to 0 otherwise (low users).

Taking the mean expected values of conditional on falling within the proper interval enables us to compute the pay gap between both groups. The difference is non-negligible; high users earn a 5.8% more than low users. Oaxaca decomposition has been traditionally used to analyze discrimination in the labour market (mainly gender and ethnic discrimination). Although our goal does not involve discrimination issues, Oaxaca decomposition is a suitable technique for exploring the source of earnings gap due to the utilization of competences. In the previous section we have confirmed that human capital and job characteristics were capturing an important component of the rewards to generic competences. This technique will allow us to discern to what extent the earnings gap is

[21] Other possible criteria are a non-weighted average of the generic competences, or weigh them using the percentage of wage variance they account for.
[22] It is a linear combination of factors which also have a mean equal to 0.

due to differences in the characteristics of the individuals and their jobs, or whether the source of the earnings gap lies in higher returns to these characteristics[23]. In other words, it will be possible to ascertain whether above-average competence users are simply more skilled and have accessed to better jobs and better firms, or on the other hand, they are more generously remunerated.

Two important technical issues have to be taken into consideration. First, the non-linearity of the estimation procedure applied in section 5. Since Oaxaca decomposition is thought as a linear decomposition, results could be biased. We prefer to estimate the model using OLS and taking again as dependent variable the expected value of log earnings conditional on falling within the proper interval. Second, there are different versions of the Oaxaca decomposition contingent on the election of earnings structures. Following Oaxaca (1973) and Oaxaca and Ransom (1994), we would use both high and low users' earnings structures. Other possibilities are the methodologies put forward by Cotton (1988), who suggested using the percentages of each type of workers as weighing proportions, Neumark (1988), who favoured a pooled structure, and Reimers (1983), who put forward an average between both structures. The generalized form of the Oaxaca decomposition is represented in (5):

$$E(W_h) - E(W_l) = (\alpha^h - \alpha^l) + (\overline{X}^h - \overline{X}^l)\beta^* + \overline{X}^h(\beta^h - \beta^*) + \overline{X}^l(\beta^* - \beta^l) \qquad (5)$$

Where, $\overline{X}^h$ and $\overline{X}^l$ represent the mean job, firm and individuals' characteristics of above-average and below-average competence workers respectively, β^h and β^l represent the coefficients of the previous characteristics, and β^* denotes the earnings structure considered. β^* takes different values contingent on the methodology applied, as summarized in Table 6. Consequently, the results will be sensitive to β^*.

Table 6. Value of β^*

Method	β^*
Oaxaca (1973): High competence workers' earnings structure	$\beta^* = \beta^h$
Oaxaca (1973): Low competence workers' earnings structure	$\beta^* = \beta^l$
Reimers (1983): Average	$\beta^* = (\beta^h + \beta^l)/2$
Cotton (1988): Weighted average	$\beta^* = \lambda^h\beta^h + (1-\lambda^h)\beta^l$
Neumark (1988): Pooled regression	$\beta^* = \beta^{pooled}$

Notes: λ^h represents the proportion of high user's; β^{pooled} is referred to the vector of coefficients obtained in the pooled estimation.

[23] We also take into account the fact that there is a part of the returns to generic competences that will be captured by the constant of the estimated equations. In part, the constants will reflect the remaining difference in earnings as a result of different degrees of utilization of generic competences that are not accounted for by the other variables.

The results of the decomposition derived from the different techniques appear in table 7. The explanatory variables replicate the full model presented in section 5. Earnings gap associated to differences of endowments (job and individuals' characteristics) are referred as the explained part, whereas earnings gap caused by differences in the coefficients is referred as the unexplained part[24]. The most interesting result of the table is that endowments appear to be the main source of the gap. However, a more in-depth analysis is required before drawing conclusions.

Table 7. Results of the decomposition using different techniques

	Oaxaca (1973) Low competence as reference	Oaxaca (1973) High competence as reference	Reimers (1983) Average	Cotton (1988) Weighted average	Neumark (1988) Pooled regression
Unexplained	0.012	-0.004	0.004	0.003	0
Explained	0.046	0.062	0.054	0.055	0.058
% unexplained	20.3	-7.4	6.4	5.1	0.2
% explained	79.7	107.4	93.6	94.9	99.8

Note: These percentages are derived from OLS regressions. Continuous log earnings estimated as the expected value of log earnings conditional on falling in the correct interval.

Table 8 breaks down the contribution of main groups of variables considered in the equation. Aiming to facilitate interpretation, the explained part (endowments) has been calculated using $\beta^* = \beta^l$, that is using the low users' earnings structure. Hence, the lowest possible value is obtained. Similarly, the unexplained part (due to coefficients) has been calculated using $\beta^* = \beta^h$, that is using the high users' earnings structure. Again, the lowest possible value is obtained. A third column indicates the proportion that is function of interaction, a fraction of which is added to the explained part and its complementary to the unexplained part, depending on β^*.

Table 8. Contribution to the earnings gap of main groups of variables

	Explained	Unexplained	Interaction
Individuals' characteristics	0,003	-0,006	0,002
Contract	0,004	0	0
Firm characteristics	0,003	0,009	0,003
Human capital measures	0,009	0,019	0,002
Job characteristics	0,029	0,014	0,006
Innovation	-0,006	0,024	0,006
Constant		-0,063	

Note: These percentages are derived from OLS regressions. Continuous log earnings estimated as the expected value of log earnings conditional on falling in the correct interval.

First, it must be noticed that the returns to job and individuals' characteristics are as important as endowments at widening the pay gap between both groups of core employees. In table 7, the effect of the unexplained was

[24] As expected, the unexplained part reaches its highest percentage when low users' earnings structure is taken as the reference; the explained part reaches its highest percentage when high users' earnings structure is taken as the reference; and the other methods provide results at some point in the middle.

overshadowed by the counteracting impact of the constant on the earnings gap. Thus, with the lowest possible endowments of job and individuals' characteristics, core employees using fewer competences would be better off than their counterparts using more competences. The situation is corrected once the endowments start to increase, due to the combined effect both endowments and returns to endowments[25]. As it can be observed, the main contributors to the earnings gap are basically human capital measures, job characteristics, and albeit non-expected, innovation variables. Firm characteristics, especially in terms of the coefficients also increase the gap. On the other hand, individuals' characteristics and contract variables do not visibly widen the differential. Probably, the most interesting result of the table is the fact that whereas the returns are the main contributor to the differential for human capital measures, the more complex job environments is the major source for job characteristics. Although to a lesser extent, the gap is also enlarged by the higher endowments of human capital of core employees using more generic competences and the returns to more complex job contents. It must be highlighted that returns to innovation variables notably increase the wage gap between the two groups of core employees.

8. Conclusions

In this paper we have examined the role of generic competences in the determination of earnings for core employees in Catalan manufacturing firms. Having access to a new and unique matched employer-employee data set which provided a self-evaluation of the content of the job in terms of 26 competences, we have been able to derive a structure of 8 generic competences which is consistent with previous research: problem-solving skills, client communication, planning skills, high-level communication, horizontal communication, numeracy skills, technical know-how and literacy skills. Furthermore, the data set provided additional information on individuals' and firm characteristics, contractual conditions, a detailed description of the workplace, and firms' attitudes towards innovation. Previous estimates of the rewards to competences could be criticized for not having properly dealt with the effect of non-observed heterogeneity. Having controlled for previously non-observed individuals', firm, and workplace characteristics, our estimates have overcome part of the bias.

[25] Despite the fact that the difference in the constants clearly appears to close the gap, it must be borne in mind that the remaining positive pay-off of generic competences exerts its influence through this difference.

The evidence emerging from hedonic wage equations signals that even after introducing all the control variables, a one-standard-deviation increase in high-level communication and numeracy skills raises earnings by around around 1%. On the other hand, a comparable and robust negative effect is derived from a similar increase in horizontal communication. The positive impact of the rest of generic competences vanishes once human capital measures (technical know-how) and workplace characteristics (planning skills and client communication) are considered. The rewards to generic competences are notably lower in comparison to previous research. This could be due, on the one hand, to our better set of control variables, and on the other hand, to the fact that our sample consists of core employees. Thus, further research in the future focusing on the pay-off to generic competences for managers is required to respond to this question. The estimation has also proved that the highest level of education attained along with experience and tenure continue to be powerful measures to predict earnings. At the same time, it has been been demonstrated that pay notoriously rises with the required time to reach the optimal level of productivity.

Fields decomposition has shown that the proportion of the wage variance explained by the generic competences drops once human capital measures and more particularly, the specific characteristics of the workplace are considered in the model. High-level and communication and numeracy skills still account for 0.8% and 0.9% of the total variance respectively nonetheless. The strong link between human capital measures together and job characteristics with generic competences has been again evidenced by the results of Oaxaca decomposition. Returns to human capital measures in addition to, more surprisingly, returns to innovation techniques, widen the pay gap between individuals whose job more intensively involves the utilization of competences and those whose job does not. The largest effect is attributable to the more demanding characteristics of the workplaces involving more generic competences nevertheless.

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Appendix

Table I: Descriptive Statistics

Earnings bands		**N**		**Percentage**	
0-700€		75		0,0359	
701€-1000€		645		0,3089	
1001€-1300€		808		0,3870	
1301€-1600€		350		0,1676	
1601€-1900€		150		0,0718	
1901€-2200€		40		0,0192	
2201€-2500€		14		0,0067	
>2500€		6		0,0029	
Individual characteristics	**N**	**Mean**	**St. dev.**	**Min**	**Max**
Female	2088	0,25		0	1
Spanish[a]	2088	0,95		0	1
Western Europe	2088	0,00		0	1
Other countries	2088	0,05		0	1
Handicapped	2088	0,05		0	1
Human capital	**N**	**Mean**	**St. dev.**	**Min**	**Max**
No education	2088	0,18		0	1
Compulsory education	2088	0,32		0	1
Vocational education (basic)	2088	0,17		0	1
Secondary education	2088	0,08		0	1
Vocational education (medium)	2088	0,16		0	1
Vocational education (higher)	2088	0,04		0	1
3-year university degree	2088	0,04		0	1
4-year university degree	2088	0,01		0	1
PhD	2088	0,00		0	1
Overeducation - high	2088	0,63		0	1
Overeducation - moderate	2088	0,17		0	1
Matched education[a]	2088	0,06		0	1
Undereducation - moderate	2088	0,13		0	1
Undereducation - high	2088	0,01		0	1
No training	2088	0,35		0	1
Experience	2088	20,61	11,15	0	49
Experience^2	2088	548,86	522,13	0	2401
Tenure	2088	9,07	8,86	0	45
Tenure^2	2088	160,83	295,53	0	2025
Contract	**N**	**Mean**	**St. dev.**	**Min**	**Max**
Non-permanent contract	2088	0,1		0	1
0-15 hours/week	2088	0,04		0	1
16-25 hours/week	2088	0,02		0	1
26-35 hours/week	2088	0,02		0	1
35-40 hours/week[a]	2088	0,84		0	1
> 40 hours/week	2088	0,09		0	1
No variable incentives	2088	0,60		0	1
Overtime pay	2088	0,14		0	1
Detailed description of the workplace	**N**	**Mean**	**St. dev.**	**Min**	**Max**
Productivity: <1 months[a]	2088	0,12	0,32	0	1
Productivity: 1-3 months	2088	0,22	0,42	0	1
Productivity: 3-6 months	2088	0,18	0,38	0	1
Productivity: 1/2-1 year	2088	0,18	0,38	0	1
Productivity: 1-2 years	2088	0,17	0,37	0	1
Productivity: >2 years	2088	0,14	0,35	0	1
Intensity	2088	3,82	0,89	1	5
Freedom to organize tasks	2088	3,43	1,16	1	5
Easy to find a similar job	2088	3,55	1,08	1	5

Table I (continued)					
Firm characteristics	**N**	**Percentage**	**St. dev.**	**Min**	**Max**
Food Industry[a]	2088	0,17		0	1
Electronics	2088	0,12		0	1
Rubber and plastic materials	2088	0,10		0	1
Metal products except machinery and equipment	2088	0,30		0	1
Machinery and equipment	2088	0,24		0	1
Furniture and other manufacturing	2088	0,08		0	1
Barcelona Metropolitan Area[a]	2088	0,54		0	1
Comarques de Girona	2088	0,14		0	1
Camp de Tarragona	2088	0,05		0	1
Terres de l'Ebre	2088	0,01		0	1
Àmbit de Ponent	2088	0,18		0	1
Comarques Centrals	2088	0,08		0	1
0-10 workers[a]	2088	0,09		0	1
11-25 workers	2088	0,34		0	1
26-50 workers	2088	0,26		0	1
51-100 workers	2088	0,17		0	1
> 100 workers	2088	0,14		0	1
Foreign participation	2088	0,06		0	1
Part of a group	2088	0,10		0	1
Family property	2088	0,81		0	1
General manager is owner	2088	0,33		0	1
% foreign sells	2088	0,15	0,20	0	0,85
Production technology, organizational practices and product innovation	**N**	**Percentage**	**St. dev.**	**Min**	**Max**
Aut. sensors input-output	1788	0,24		0	1
Aut. warehouse management	1828	0,26		0	1
Flexible production systems	1801	0,48		0	1
Artificial sight controls	1808	0,12		0	1
Aut. quality control systems	1870	0,26		0	1
Assisted production (robots)	1843	0,33		0	1
Internal net of data exchange	1859	0,73		0	1
CAE	1819	0,47		0	1
Workers' suggestions	1839	0,14		0	1
Sharing information managers-workers	1859	0,71		0	1
Job rotation	1877	0,58		0	1
Redesign of workplace	1853	0,43		0	1
Teams of problem-solving	1820	0,36		0	1
Semiautonomous groups	1815	0,28		0	1
Quality circles	1805	0,49		0	1
TQM	1735	0,29		0	1
Product innovation (in the last 2 years)	1976	0,74		0	1

[a] Denotes referential variables in regressions

Table II. Initial set of competences

Dealing with people	Instructing, training, teaching people, individually or in group
Selling a product or a service	Reading short documents such as short reports, letters or memos
Counselling, advising or caring for customers or clients	Writing long documents such as long reports, handbooks, articles or books
Making speeches or presentations	Calculations using decimals, percentages or fractions
Persuading or influencing others	Calculations using advanced mathematical or statistical procedures
Planning the activities of others	Spotting problems or faults
Delegating tasks	Working out the cause of problems or faults
Planning your own activities	Thinking of solutions to problems
Organizing your own time	Noticing when there is a mistake
Thinking ahead	Paying close attention to details
Learning continuously	Usage of computer or any sort of electronic equipment
Working with a team of people	Knowledge of particular products or services
Listening carefully to colleagues	Specialist knowledge or understanding