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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. 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 the returns to generic competences differ depending on the position of the worker in the firm. Only numeracy skills are reward independent of the occupational status of the worker. The level of technology used by the firm in the production process does not directly increase workers' pay, but it influences the pay-off to some of the competences.

JEL Classification: J24, J31

1. Introduction

Researchers have reported the deep transformations taking place in the labour market during the last decades. These changes, mainly attributed to technological change and the advent of the knowledge society, have pervaded the nature and content of jobs and have altered the returns to human capital. As a result, wage inequality has increased within education levels since the 70's (Acemoglu, 2002). Wage inequality within education levels, also known as residual inequality can be attributed, among other factors, to the expansion of the concept of human capital, not restricting it to education and experience, and differences in the pay-off to human capital depending on firm characteristics, which make it more or less productive.

Researchers have augmented traditional mincerian wage equations with the inclusion of generic competences in order to estimate their pay-off. Empirical evidence shows that workers obtain substantial gains from the utilization of generic competences in their workplaces. Following previous research, we aim to assess the returns to workers' qualifications, expanding the concept of human capital with the introduction of generic competences as explanatory variables of wages. Thus, we will able to determine the value of each of these generic competences, and discuss which of them make the worker more productive. The level of technology is another element that should exert a decisive influence on wages through worker's productivity. Dalmazzo (2002) demonstrated that the differences between firms in the complexity of technology creates significant pay differences for similar workers. We aim not only to address the direct impact of the production technology on wages, but also whether the returns to generic competences are higher in more technologically advanced firms.

Existing empirical evidence regarding the impact of generic competences on wages is scarce and presents several caveats. Given the difficulties to generate suitable data sets combining information on workers' and firm characteristics, evidence on the impact of technology on the returns to individuals' human capital is even scarcer. Fortunately, we have a matched employer-employee data set which offers wide and detailed information on individuals', firm and workplace characteristics. With respect to human capital, workers were asked to measure the utilization they made of a list of 26 generic competences, which are based on the Skills Survey of the Employed British Workforce so that our results are comparable to those using data drawn from that survey. Among the questions related to firm characteristics, general managers were asked to indicate which production technologies were involved in the production processes of their firms.

The characteristics of the data set help to mitigate the empirical problems faced in previous studies examining the pay-off to generic competences. Our main concern is related to the proper control for firm characteristics. Failing to do this would result in biases if variables related to individuals partially capture the effect of the omitted firm characteristics. Matching detailed information on firms with the individual-level data should help to more effectively attenuate these potential biases in comparison with previous studies as well as giving more approximate estimates of the real returns to human capital.

The remaining of the paper is laid out as follows. In next section we review the literature addressing the returns to generic competences. In section 3 we describe the survey we draw our data from. In Section 4 we develop the indexes that measure the utilization of generic competences. In section 5 we estimate the returns to generic competences. In section 6 we analyze whether the returns to generic competences differ depending on the technology used by the firm. Finally, we present the main conclusions in section 7.

2. Previous research

The concept of human capital has been at the forefront of the academic debate in economics during the last 4 decades. According to the principles of the human capital theory (Becker, 1964) human capital is acquired through education and experience, which increase workers' productivity. In opposition to this argument, Thurow (1975) advocated that education is useless to increase workers' productivity, as it only functions as an indicator of skills and abilities.

Empirical evidence has repeatedly reported remarkable wage premiums for educated workers. However, researchers have been concerned from the very beginning about the effect of omitted individual ability and skills on the estimate of the pay-off to education. This premium partially reflects individual abilities and skills that are not acquired through education. In the last decades, earning differentials within educational levels have widened. At the same time, there is evidence that skills and abilities are gaining more and more importance in jobs (Dickerson and Green, 2004). Some researchers have set their sights on measuring the rewards to the utilization of these skills and abilities in the workplace to disentangle them from the returns to education. Suleman and Paul (2006) distinguish 2 generations of studies. The first one consists of those which introduce cognitive skills measured by means of tests providing comparable scores. A second generation of studies obtains subjective measures of the utilization of skills by directly asking employees or employers.

Despite the fact that most research finds that the utilization of some of the skills results in a better pay, the agreement vanishes when specifying which of them make the worker more productive. The first disagreement is related to the discussion about the effect of cognitive skills. Murnane *et al.* (1995) signaled the growing importance of cognitive skills in the determination of wages. Subsequent papers also found positive returns to this type of skills (Tyler *et al.,* 1999; Freeman and Schettkat, 2001; McIntosh and Vignoles, 2001; Green *et al.*, 2002; Denny *et al.*, 2003; Johnes, 2005).

On the other hand, Bishop (1995) affirmed that cognitive skills are crucial to develop occupation specific skills, from which productivity derives. Thus, cognitive skills act as tools which enable the acquisition of occupation specific skills, but do not substitute them. Heijke *et al.* (2003) distinguished between management competences, discipline-specific competences and general academic competences. Only management competences, directly related to the job, carried a positive pay-off. However, discipline-specific skills were essential to find a job within the domain of studies and general academic competences played a supportive role to learn management competences. Also Mañé (1999) and Bishop and Mañé (2004) came to similar conclusions. Dickerson and Green (2004) and Johnson (2006) found negative returns to number and mathematical abilities respectively.

In the recent years, researchers have accessed more detailed data sets drawn from surveys in which workers or employers were asked to what extent the utilization of a certain competence was involved in a job. On the one hand, this has prompted researchers to attempt to decipher which generic competences are more valued by employers. The positive impact of generic competences on wages has been well documented in previous research (Green, 1998; Dickerson and Green, 2004; Garcia Aracil *et al.*, 2004; Johnes, 2005; Suleman and Paul, 2007), although some of them entail a drop in earnings. These authors augmented traditional mincerian equations by introducing generic competences, which are regarded as job attributes that need to be compensated by employers. On the other hand, the fact that the sources of information are far from being homogenous has led to discrepancies in the generic competences considered. The main inconvenient is the lack of comparability between the results of different studies, as it is shown in table 1. Fortunately, specifically designed surveys have contributed to mitigate this problem. Green (1998), Dickerson and Green (2004) and Johnes (2005) have drawn their data form the Skills Survey of the Employed British Workforce.

Table 1: Generic competences considered in previous studies

Green (1998)			**Dickerson and Green (2004)**		**Garcia Aracil *et al.* (2004)**		**Johnes (2005)**		**Suleman and Paul (2007)**		
Skills	**Fe**	**Ma**	**Skills**	**All**		**All**		**All**		**Fi**	**V**
Verbal	+	ns	Literacy	ns	Participative	+	Physical	-	Cognitive	+	+
Manual	-	-	Physical	-	Methodological	+	Strategy and HR	+	Strategic	+	+
Problem-solving	+	+	Numerical	-	Specialized	ns	IT	+	Behaviour towards org.	ns	+
Numerical	ns	ns	Technical know-how	+	Organizational	-	Quantitative	+	General knowledge	+	ns
Planning	ns	ns	High-level com.	+	Applying-rules	-	Teamwork	+			
Client Com.	ns	ns	Planning	+	Physical	-	Oral com.	+			
Horizontal com.	ns	ns	Client com.	-	Generic	+	Self-motivation	+			
Professional com.	+	+	Horizontal com.	ns	Socio-emotional	+	Written com.	+			
			Problem-solving	ns			Advanced analytical	+			
			Checking	ns			Problem solving	-			
			Computer	+							

Abbreviations: Fe (female); Ma (Male); Fi (Fixed pay); V (Variable pay); com. (communication); org. (organization)
Symbols: + denotes positive significant impact on earnings; - denotes negative significant impact on earnings; ns denotes not significant impact on earnings.

Another issue of concern is the fact that, whereas generic competences are primarily acquired within the working environment (Heijke *et al*, 2003; Mañé and Miravet, 2007), data sets previously used mainly focused on individuals' data, partially neglecting firm characteristics. Besides, the value of generic competences responds to the interaction process of their supply and demand mechanisms. Certainly, the demand of generic skills is determined by firm characteristics. The omission of proper controls for the demand side could result in biases if the returns to generic competences are capturing part of the return to firm characteristics to which are correlated. Matching individual with firm data is the solution we suggest in this article.

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 (food products and beverages, electrical and optical equipment, rubber and plastic products, fabricated metal products, except machinery and equipment, machinery and equipment, and furniture) and 3 sectors of the service industry (hotels and restaurants, computer and related activities, and health and social work). These firms 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[1]. Four types of questionnaires were delivered, depending on the position in the firm: general manager, managers, supervisors and core employees[2]. The questionnaires distributed among general managers asked for detailed information on

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

[2] Core employees are defined as those base workers who specifically take part in the production process to obtain the main output produced by the firm. Thus, workers engaged in other areas of the firm such as marketing, accounting, administration are excluded from this category.

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 for managers, supervisors and core employees consisted of a detailed investigation on the nature and content of their jobs. Questions ranged from human capital and other specific characteristics of the worker, to an in-depth 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).

The special characteristics of the survey allow us to introduce certain improvements with respect previous papers. First, our survey pursues comparability with the Skills Survey of the Employed British Workforce, and more particularly with the questions regarding competences. The reason to do so is because its data has been already used by Green (1998), Dickerson and Green (2004) and Johnes (2005). Competences are not likely to fully coincide because of the statistical techniques applied on the data. However, the final structure of generic competences should be similar, favoring comparability. Second, the clear distinction between positions (managers, supervisors and core employees) will enable us to ascertain whether the pay-offs to generic competences are sensitive to the position of the firm. Previous papers implicitly assume that rewards are equal for all the workers in the firm. We will run different estimations for each group with the object of checking whether the value of competences is the same irregardless of the rank of workers. Third, since the data set matches information on individuals with information on firms we are able to control for some firm characteristics that have been neglected in previous research. Since, the learning of generic competences partially takes place within the working environment, estimates of their pay-offs are likely to be biased by the effect of omitted variables. The better control for demand-size variables should give rise to more precise estimates of the returns to the supply-side variables[3].

3.2 Descriptive statistics

The initial sample comprises 4836 workers in 475 firms. Because of missing values, the final sample contains 4271 observations that are related to 463 firms; 569 out of which are managers, 607 supervisors, and 3095 core employees.

A summary of both dependent and independent variables by rank in the firm is provided in Table I in the Appendix. As expected, there are marked differences in earnings between managers, supervisors and core employees. 69% of the core employees report being within the 2[ond] and 3[rd] interval, that means earning between 700€ and 1300€ per month[4]. Half of the supervisors are also concentrated within the 2[ond] and 3[rd] interval, with a monthly pay ranging from 1000€ to 1600€. Finally, almost the 60% of managers earn less than 2600€.

The sample is basically composed by men, reflecting men predominance in the industries considered. It must be noted that the percentage of women decreases with positions of higher responsibility in the firms. The percentage of immigrants is around

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[3] Groshen (1991) found that a non negligible part of wage variation was due to firm effects. Subsequent studies followed the methodology she had devised. Likewise, all of them come to the conclusion that a considerable proportion of wage variation was due to between firm variation (Mizala and Romaguera, 1998; O'Shaughnessy *et al.*, 2001, Simón, 2005; Lane *et al.* 2007).

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

4%. It shows different patterns depending on the position in the firm. That is, the largest percentage of non-Spanish workers is for core employees, primarily from non-western countries. The lowest percentage is for supervisors. Non-Spanish workers in managers' positions mainly originate from Western countries. The level of education is relatively low, since a 47% in the whole sample has completed at the most compulsory education or basic vocational education[5]. Not surprisingly, this percentage plummets to 10% for managers. It remains as the larger group for supervisors (37%) nonetheless. The proportion of individuals who have successfully achieved at least a 4-year-degree is low, with the sole exception of managers (33%). The majority of the respondents have a permanent contract (88%). and work between 35 and 40 hours per week (77%). Job stability and working hours increase with the position within the firm. Activity is mainly located in the Metropolitan Area of Barcelona[6]. Firms participating in the survey are small- and medium-sized firms and their average number of workers is 35. The average percentage of exports is 16%.

4. Analysis of competences

4.1 Generic Competences for managers, supervisors and core employees

Workers had to examine to what extent their jobs involved a set of 26 competences, which are shown in table 2[7]. Respondents were asked to evaluate the importance of each

[5] Education level 1 encompasses no education at all, Compulsory education and basic vocational education. Education level 2 comprises secondary education and medium vocational education. Education level 3 includes 3-year-university degrees and higher vocational education. Education level 4 denotes 4-year-degrees and PhD. The distinction between 3-year-degrees and 4-year-degrees must be noted.

[6] The Metropolitan Area of Barcelona is an area of high density of population and economic activity. The rest of jobs are located in the other 3 Catalan provinces (Girona, Lleida and Barcelona) and the remaining part of the province of Barcelona not included in the Metropolitan Area.

[7] The survey explicitly asked workers about the content of the jobs. The answer to this question could be also considered an evaluation of the competences that each employee has at the time of the survey. Nonetheless, as Dickerson and Green (2004) put forward, this latter approach entails a certain bias due to possible mismatches between job requirements and workers' skills. For instance, consider the case of a highly qualified employee eager to assume more demanding activities, despite being stuck due to the lack of perspectives of being promoted. Conversely, consider the case of an employee who is not able to meet

competence. The range of possible answers included “not important at all”, “not very important”, “fairly important”, “very important” and “essential”. The competences needed to be reduced into an easier to interpret set of generic competences. Factor analysis is used with this object. Factor analysis is a well known statistical 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 other words, the factors can be used to measure to what extent certain groups utilize generic competences.

Table 2. 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	Knowledge of particular products or services
Working with a team of people	Specialist knowledge or understanding
Listening carefully to colleagues	Use of computer equipment

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”[8]. Factor analysis is then applied. It is necessary to rotate the factors obtained in order to aid interpretation. An orthogonal rotation[9] has been applied to the data. Table 4 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

the demands of his jobs, and cannot be demoted. These biases grow with the labour market rigidities. The more barriers to job mobility, the larger the probability of mismatches.

[8] We have excluded the use of computer equipment because we prefer to assess its impact on earnings separately. Hence, we apply factor analysis on the remaining 25 competences.

[9] 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.

criteria of the researcher, although there are some rules that are recommended to follow. According to the 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 not have reached 66%. Nonetheless, the eigenvalue of the 6th factors is close to 0.95, the eigenvalue of the 7th factor is 0.85, and the eigenvalue of the 8th factor is 0.71. Once these 3 additional factors are considered, the percentage of explained variance goes up to almost 76%.

Table 4 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[10]. Second, the internal consistency of the factors measured by the Cronbach's Alphas was rather high[11]. And finally, each variable appears related at most to one factor (figures in bold in Table 4)[12]. 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. Interestingly, this structure is

[10] 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.

[11] 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.

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

fundamentally consistent with the one obtained by Dickerson and Green (2004), with the difference that they had a further category, they called checking skills, which appears in table 4 as a part of problem solving. Generating the factors is the last step of the procedure, for which, the regression technique was used[13]. The final distribution of the 25 competences across the new factors is as follows:[14]

Table 3. Classification of competences emerging from factor analysis	
Spotting problems or faults Working out the cause of problems or faults Thinking of solutions to problems Noticing when there is a mistake Paying close attention to details	**Problem solving**
Dealing with people Selling a product or a service Counselling, advising or caring for customers or clients Making speeches or presentations	**Client communication**
Persuading or influencing others Planning the activities of others Delegating tasks	**High-level communication**
Planning your own activities Organizing your own time Thinking ahead Instructing, training, teaching people, individually or in group	**Planning skills**
Dealing with people Learning continuously Working with a team of people Listening carefully to colleagues	**Horizontal communication**
Calculations using decimals, percentages or fractions Calculations using advanced mathematical or statistical procedures	**Numeracy skills**
Knowledge of particular products or services Specialist knowledge or understanding	**Technical knowledge**
Reading short documents such as short reports, letters or memos Writing long documents such as long reports, handbooks, articles or books	**Literacy skills**

[13] 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.

[14] There is a 9th category not included in the table, Computer skills, which is not derived from the factor analysis.

Table 4. 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	0.1221	**0.4052**	0.1956	0.264	**0.4037**	0.0193	0.046	0.0513	0.5448
Selling	0.0622	**0.7719**	0.1617	0.1118	0.0914	0.1044	0.0529	-0.013	0.3394
Advising	0.111	**0.7674**	0.1839	0.1416	0.132	0.0896	0.1465	0.058	0.2946
Presentations	0.0979	**0.5868**	0.3213	0.0875	0.0948	0.1787	0.0997	0.3129	0.3864
Persuading	0.1117	0.3631	**0.5472**	0.1497	0.1173	0.0925	0.0941	0.1915	0.466
Planning others	0.1754	0.1924	**0.7323**	0.2012	0.1178	0.1226	0.0908	0.0521	0.3157
Delegating	0.2023	0.2572	**0.6861**	0.2386	0.1544	0.1448	0.0559	0.0344	0.3162
Planning ownself	0.2488	0.1566	0.2806	**0.7111**	0.1499	0.1094	0.1007	0.0325	0.2836
Organizing own time	0.2734	0.1317	0.1757	**0.7302**	0.1809	0.0889	0.0821	0.0451	0.2945
Thinking ahead	0.3235	0.2494	0.1401	**0.4427**	0.3363	0.1569	0.0635	0.1064	0.4644
Learning continuosly	0.3899	0.1843	0.0639	0.3326	**0.4781**	0.1467	0.1355	0.0668	0.4263
Working with people	0.2561	0.1525	0.2396	0.2244	**0.6132**	0.022	0.1219	0.018	0.4117
Listening	0.3145	0.1463	0.1611	0.1957	**0.6308**	0.0377	0.1051	0.0921	0.3966
Teaching	0.3751	0.2346	**0.4002**	0.1566	0.3619	0.1096	0.0647	0.0651	0.4682
Reading short	0.1871	0.2802	0.218	0.1688	0.2156	0.2605	0.2211	**0.4122**	0.4774
Reading long	0.1374	0.2721	0.2659	0.0957	0.1107	0.3618	0.2122	**0.4437**	0.4422
Simple calculations	0.2463	0.0945	0.1198	0.1154	0.0318	**0.6931**	0.0951	0.0392	0.4107
Complex calculations	0.2449	0.1686	0.1427	0.0991	0.0449	**0.7122**	0.1036	0.088	0.3538
Spotting problems	**0.7775**	0.0435	0.1128	0.1342	0.1198	0.1816	0.0547	0.021	0.3122
Cause of problems	**0.7795**	0.0978	0.1955	0.1428	0.0894	0.1629	0.096	0.0843	0.2733
Solution to problems	**0.7734**	0.1494	0.1691	0.2007	0.1482	0.1444	0.1108	0.0513	0.2529
Noticing mistakes	**0.8206**	0.0416	0.0708	0.12	0.1154	0.0595	0.0657	0.0157	0.2841
Detail	**0.6218**	0.0334	-0.0368	0.1351	0.2281	0.055	0.1238	0.0128	0.5221
Knowledge of products	0.2858	0.2932	0.1659	0.1633	0.1476	0.1631	**0.553**	0.0611	0.4203
Specialist knowledge	0.3171	0.208	0.1297	0.1743	0.1848	0.2498	**0.5552**	0.1459	0.3829

Taxonomy of the generic competences	**Problem solving**	**Client communication**	**High-level communication**	**Planning skills**	**Horizontal communication**	**Numeracy skills**	**Technical knowledge**	**Literacy skills**
Standard deviation	0.9249	0.8627	0.8385	0.8312	0.7922	0.8069	0.6991	0.6233
Cronbach's Alpha	0.9031	0.8224	0.8374	0.8263	0.8044	0.8165	0.7944	0.7349

Notes: Factor analysis applied on 4271 observations (core employees, supervisors and managers). Factors have been orthogonally rotated.
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.

Some of the original competences keep relatively high loadings, between 0.35 and 0.4, with respect to other factors. This is the case of learning continuously and teaching with problem solving skills; persuading with client communication; or reading long documents with numeracy skills. It is attributable to the fact that these competences are involved in a diversity of types of activities in the workplace. These relatively strong relationships are also captured by the new factors.

4.2 The utilization of generic competences

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 5 depicts the situation by gender, the highest level of education attained, and technology level of the firm.

By gender, a distinct pattern of competences emerges. That is, men are more involved in problem-solving, high-level communication, and numeracy activities. Alternatively, women activities are more related to client communication, planning, horizontal communication, technical know-how, literacy skills, and more surprisingly, the use of computer equipment. The table also reveals that, as expected, the higher the level of education attained, the higher deployment of competences. All the factors except problem solving and horizontal communication present a perfect monotonical increasing trend. Individuals having completed secondary education or medium vocational education work in jobs involving the highest level of problem solving competences. Utilization of horizontal communication competences is highest for individuals having completed a 3-year-degree or higher vocational education.

We classify firms into 2 categories, high-tech and low-tech firms so as to examine whether there is a different use of competences depending on the production technology. We establish the border between both categories at the median of each sectors' continuous measure of the technology index. The firm technology index appears to be intimately linked to the utilization of competences. Jobs in high-tech firms involve a more intensive use of all generic competences with the sole exception of client communication competences. It reflects that high-tech firms employ more qualified human capital than low-tech firms[15]. The differences in the utilization of competences between both types of firms are particularly high in terms of high level communication, problem-solving skills and computer use.

Table 5: Mean levels of generic competences by gender, highest education level attained, and technology level

	Sex		Highest educational level attained				Technology	
	Men	**Women**	**Educ. 1**	**Educ. 2**	**Educ. 3**	**Educ. 4**	**Low-Tech**	**High -Tech**
Obs.	2932	1339	2005	1074	803	389	2382	1889
Prob. solv.	0.034	-0.075	-0.019	0.061	0.012	-0.097	-0.056	0.070
Client com.	-0.039	0.086	-0.098	-0.027	0.175	0.220	0.033	-0.041
High com.	0.067	-0.147	-0.113	-0.031	0.110	0.442	-0.053	0.066
Planning	-0.018	0.040	-0.057	0.010	0.063	0.133	-0.009	0.012
Horiz. com.	-0.057	0.124	-0.046	-0.003	0.107	0.025	-0.015	0.020
Numeracy	0.065	-0.142	-0.109	0.049	0.103	0.213	-0.009	0.012
Tec. know.	-0.009	0.020	-0.198	0.076	0.259	0.276	-0.019	0.024
Literacy	-0.017	0.037	-0.128	-0.057	0.195	0.414	-0.016	0.020
Computer use	-0.059	0.129	-0.426	0.188	0.512	0.619	-0.069	0.086

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

Table 6 explores to what extent competences are related to the position within the firm and the time workers need to reach the optimal level of productivity. With respect to the position in the firm, it is apparent that core employees have the lowest levels of utilization for all the competences. We would expect that managers would be using competences more intensively in comparison with supervisors. However, supervisors' jobs involve a

[15] Doms *et al.* (1997) found that more advanced technological firms had more qualified employees. However, they suggested that prior to the adoption of technology, these firms already had a more qualified labour force.

higher level of problem solving, higher communication, planning, and horizontal communication competences. The level of utilization of competences turns up to be monotonically increasing with the time needed to be productive at job, being this latter measure an indicator of the complexity of the job. There are some exceptions, being the most remarkable the use of computer equipment[16], which presents an inverted U reaching its top between 6 months and a year. Undoubtedly, the table points out that more complex jobs and higher levels of responsibility require a more intensive use of competences from workers.[17].

Table 6. Mean levels of generic competences by position in the firm and required time to reach the optimal level of productivity

	Position in the firm			Time needed to reach the optimal level of productivity					
	Manager	**Supervisor**	**Core employee**	**< 1 Month[a]**	**1-3 months**	**3-6 months**	**1/2-1 year**	**1-2 years**	**> 2 years**
Obs.	569	607	3095	387	813	768	893	726	684
Prob. solv.	-0.002	0.186	-0.036	-0.305	-0.139	-0.011	0.096	0.100	0.119
Client com.	0.280	-0.015	-0.049	-0.014	-0.102	0.008	-0.007	0.043	0.083
High com.	0.640	0.709	-0.257	-0.392	-0.237	-0.078	0.064	0.223	0.272
Planning	0.165	0.202	-0.070	-0.206	-0.076	-0.009	0.016	0.037	0.158
Horiz. com.	0.001	0.047	-0.009	-0.031	-0.007	-0.071	0.049	0.020	0.021
Numeracy	0.340	0.082	-0.079	-0.345	-0.181	0.003	0.032	0.143	0.213
Tec. know.	0.158	0.092	-0.047	-0.270	-0.060	0.070	0.058	0.045	0.022
Literacy	0.228	0.040	-0.050	-0.100	-0.065	0.033	0.058	0.054	-0.036
Computer use	0.582	0.297	-0.165	-0.535	-0.161	0.074	0.159	0.124	0.071

[a] This group is only considered for core employees.
Abbreviations: Problem-solving (Prob. solv.), Client communication (Client com.), High-level communication (High com.), Horizontal communication (Horiz. com.), Technical know-how (Tec. know.).

4.3 The Other job characteristics

It is also noteworthy to explore other dimensions of workplaces. We have built indexes for managers and supervisors that measure the degree of freedom to organize, the relevance of

[16] Other exceptions are: jobs involving a maximum level of client communication competences, technical know-how, and literacy skills require a period between half year and a whole year so that workers reach the optimal degree of productivity.
[17] 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.

workers' initiative and the importance of exchanging ideas by applying factor analysis to the responses of workers to a sub-group of questions in the survey[18] The questionnaire for core employees only allows us to develop an indicator of the degree of freedom to organize[19]. An indicator of the degree of intensity of the job has also been developed for the whole sample[20]. The table makes apparent that the highest degree of intensity is for managers and the lowest for core employees. Managers' jobs encompass a higher degree of freedom to organize tasks. Similarly, initiative and exchanging ideas are more present in managers' jobs, although the differences are much smaller to the point that differences are marginal in the case of exchanging ideas.

Regarding complexity of computer use, we have no information available for core employees. Managers and supervisors were asked to indicate which of the following answers better matched the use they made of computer equipment: not using, simple, moderate, complex and advanced[21]. For both managers and supervisors, the most common

[18] A first set of questions asked managers and supervisors to indicate to what extent they agreed to the statements that affirmed that in the job they performed they had a high degree of responsibility, independence and freedom to make mistakes and learn from those mistakes; they were entitled to make decisions and solve problems without asking to their superiors; they enjoyed a great level of freedom to manage the resources of the department; their superior encouraged them to develop new initiatives within the department; their superior encouraged them to take controlled risks; and they could be rewarded and be recognized for implementing new initiatives in the department. The scale of answers ranged from 1 (total disagreement) to 5 (total agreement). We have obtained 2 indicators from this first set of questions: freedom to organize and initiative. We have derived the third factor, exchanging ideas, from the questions which asked managers and supervisors to indicate to what extent they agreed with the statements that affirmed that they had to exchange ideas with other colleagues very often to solve problems and generate new opportunities; and it was important to learn everyday from one another by means of the exchange and the combination of ideas. The scale was identical.

[19] The index that measures the degree of freedom to organize for core employees has been developed from the question that asked them to indicate to what extent they agreed with the statement that affirmed that they had a lot of freedom to decide how they organized the tasks they performed. Since it is based on just 1 question, we have standardized the variable. The main drawback of computing this variable separately for core employees is the fact that it prevents comparisons with managers and supervisors.

[20] Replicating the structure of the preceding questions, workers were asked to indicate to what extent they agreed with the statement that affirmed that their job demanded that they worked very intensively.

[21] The categories are described as follows: I don't use computer equipment very often (not using); checking e-mail and searching information on the internet (simple); using text processors, spreadsheets (moderate); using computer for analyzing or designing (complex); use of computer syntaxes or programming (advanced). In the econometric models in the next section we simplify these 5 categories in 2 groups. The first category is labelled as basic users and includes non users, simple and moderate users. The second category, labelled as

use of computers is related to text processors, spreadsheets... Differences emerge at the bottom and the top of the distributions. The number of managers who do not often use computer equipment or have a simple use of it is rather low in comparison with those reporting a complex or advanced use. Conversely, the percentage of supervisors reporting a complex or advanced use of computer equipment does not exceed the percentage of simple and non-users.

Table 7. Other job characteristics by position in the firm. Intensity, freedom to organize and complexity of computer use.

	Total Sample			Managers			Supervisors			Core employees		
	N	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**
Intensity	4271	0.00	1.00	569	0.26	0.84	607	0.20	0.85	3095	-0.09	1.04
Freedom to organize[a]	3095	0.00	1.00							3095	0.00	1.00
Freedom to organize[a]	1176	0.00	0.72	569	0.18	0.70	607	-0.17	0.69			
Initiative	1176	0.00	0.76	569	0.11	0.71	607	-0.11	0.79			
Exchanging ideas	1176	0.00	0.77	569	0.03	0.76	607	-0.03	0.78			
Complexity of computer use												
Not using (computers)	1176	0.12		569	0.03		607	0.19				
Simple use	1176	0.07		569	0.05		607	0.10				
Moderate use	1176	0.43		569	0.42		607	0.43				
Complex use	1176	0.28		569	0.36		607	0.20				
Advanced use	1176	0.10		569	0.13		607	0.08				

Notes: Means reflect percentages in dummy variables. No standard deviations for dummy variables are shown.
[a] This variables is computed in different ways depending on the position within the firms.

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 as 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):

$$\ln W_i = \alpha + Comp_i \beta + Ind_i \delta + Firm_i \phi + Job_i \gamma + + \upsilon_i \quad (1)$$

not basic users, contains the two remaining groups. The percentage of workers in each of the categories is shown in the Appendix I.

Where, the dependent variable ($\ln W_i$) is the logarithm of earnings, the set of nine generic competences is represented by the matrix $Comp_i$, *Ind* denotes individuals' control variables including human capital, $Firm_i$ comprises the characteristics of the firm, also the level of production technology, Job_i captures the content and the characteristics of the contract of the workplace in detail, and finally, υ_i denotes the error term of the model[22].

The inclusion of these variables is based on the relevant empirical evidence given by previous studies. The fundamental novelty is the quality of both individual and firm level control variables, which are introduced simultaneously in the equation. Since we have been able to match information on both the demand and supply side of labour, independent variables of the model comprise a better than usual list of controls at individual, firm and job level. Taking into consideration the unavoidable links between individual and firm characteristics, the inclusion of the extended list of controls allows a closer approach to the real pay-off to generic competences. However, we must note that our cross-sectional equation cannot completely overcome the biasing effect of individual and firm non-observed heterogeneity nevertheless, since part of it is likely to remain.

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 for each individual 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

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

continuous, although unobserved dependent variable, and estimate the model by Maximum Likelihood. We assume that our earnings variable is log-normally distributed[23]. The estimator is in fact a generalization of the Tobit model.

The outcomes of regressions for managers, supervisors and core employees are respectively presented in tables 8, 9 and 10. First and being consistent with previous research, some generic competences carry positive and non-negligible returns. Second and confronting previous research, it stands out that the returns to generic competences considerably vary with the rank of the worker[24]. In other words, employers are prone to offer pay-offs to different competences depending on the position the worker holds in the firm. Besides, the amounts of the pay-offs increases with the position of the worker within the firm.

In the case of managers, client communication competences are the most valued by employers as a one-standard-deviation increase confers a 6.84% increase in earnings[25]. We firmly believe that such large returns are related to the signature of strategic commercial sells for firm overall performance, the responsibility of which lies in some managers. Numeracy skills are rewarded more modestly, and their coefficient is no longer significant when we add other job characteristics to the model. In contrast with these positive returns, there is a large penalization to literacy skills for managers. Client communication and numeracy skills also carry a positive pay-off for supervisors, although in the case of the former this is not as large as the managers' pay-off. Finally, for core employees higher

[23] This seems a reasonable assumption, except for the highest interval, in which a Pareto distribution seems more plausible.
[24] We consider as "previous research" recent studies that augment the traditional mincerian wage equation with the introduction of generic competences.
[25] This increase is calculated as exp(0.0767 X 0.8627) – 1 = 6.84%, being 0.8627 the real standard deviation of the variable.

communication skills, planning skills as well as numeracy skills are the most valued competences by employers. Dickerson and Green (2004), Garcia Aracil *et al.* (2004) and Johnes (2005) also reported a large and positive impact on earnings attached to competences which encompass high-level communication and planning skills [26]. Interestingly, a significant, although modest, penalization to horizontal communication skills emerges once we control for additional job characteristics. Less experienced core employees' jobs are more intensive in horizontal communication skills when compared to more experienced core employees. Their learning-by-doing process is likely to be tutored by some more experienced co-workers. This learning process, which is less common at higher levels of the firms, inflates the utilization of horizontal competences and accounts for the negative coefficient.

We interpret these results as the outcome of the interaction between the demand and the supply of generic competences. For instance, client communication skills at the highest positions in the firm, as they are central to firm performance, must be very appreciated by employers. Their large premium is thus explainable in the grounds of a scarcity of these skills to satisfy firms' needs. Likewise, higher-communication and planning skills are presumably not very common among core employees. Hence, they confer a remarkable advantage to those individuals who have acquired them and regularly deploy them in their jobs. On the other hand, we provide clear empirical evidence that numeracy skills are important whichever the position of the worker in the firm and after having controlled for a large range of other generic skills and job characteristics. This result gives support to those studies which advocate for the importance of cognitive skills, for instance Johnes (2005),

[26] Johnes (2005) introduced a single variable which comprises human resource management and strategic planning skills. Garcia Aracil *et al.* (2004) labelled as participative skills a group of skills which encompassed planning, negotiating, leadership, initiative, personal involvement, assertiveness decisiveness and persistence, and taking responsibilities.

and opposes to Dickerson and Green (2004). The non-significant impact of problem-solving skills is in accordance with the findings of Garcia Dickerson and Green (2004), whereas Johnes (2005) reported a negative impact on earnings. In opposition to both studies, and in likeness with Zoghi and Pabilonia (2005), we find that placing a computer on the workers' desk does not make any difference in pay when we control for human capital and other skills.

We must highlight the fact that the returns to generic competences in our sample are clearly below those reported in the UK. We hypothesize 2 possible reasons; first, estimates of the returns to generic competences in previous papers were inflated due to the action of omitted variables, or otherwise, generic competences are not as present in the Spanish pay scheme as they are in the UK. Not shown in the table, we have reestimated the model with a shorter range of controls so as to mirror prior specifications[27]. We come to the conclusion that coefficients attached to the generic competences do not experience significant changes[28]. As a result, we come to the conclusion that generic competences are far less important determinants of pay schemes in comparison with the UK.

Turning to other job characteristics, results portray a positive pay-off to the degree of freedom experienced in the job for managers, supervisors and core employees, although it declines with these lower positions. This result conforms to theories predicting higher wages when jobs are difficult to monitor. Conversely, intensity turn up to be

[27] We have dropped the firm technology index, the dummy variable that signals whether the firm is part of a group, the percentage of exports and the dummies that signal whether the worker has undertaken a MBA (managers) or training provided by the firm (supervisors and core employees) and whether the workers works longer than 40 hour per week.

[28] In fact, only the dropping of the dummy variable that indicates that the worker spends more than 40 hours per week working yields a slight increase in some of the returns to the competences.

unremunerative, whereas initiative is only rewarded to managers. Finally, in the case of supervisors, jobs involving exchanging ideas are worse paid.

What is more surprising is the non-significant impact of complex and advanced computer skills for managers[29]. Nevertheless, a positive impact emerges if we consider advanced users as a separate group[30], thereby signalling that there is only a premium for managers at a very advanced level of computer skills. On the other hand, supervisors whose job demands for complex and advanced computer skills have a premium. These results suggest that there could be a threshold beyond which the utilization of computer skills is rewarded by employers. Our evidence is far from being strong enough to assert this result.

With respect to the rest of human capital measures, the tables show that education and experience still carry a large and consistent premium. We must note that the higher the rank in the firm, the larger the gap between education levels and the larger wage differences due to experience. Rewards to tenure are not as large as rewards to experience. Besides, it is apparent that supervisors are not better paid for a longer tenure. Neither are they for having received training by the firm, which contrasts with the positive returns to the training undertaken by core employees. Finally, managers' pay is boosted by having completed a MBA program.

The most striking result regarding firm characteristics is given by the production technology index, which has no significant effect on supervisors' and core employees' earnings. Even worse; it noticeably depresses managers' earnings. We have re-estimated the model using an alternative definition of the technology variable by classifying firms in

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[29] We are comparing a group which encompass non-users, simple and moderate use users with a second group which comprises complex and advanced users

[30] Not shown in the tables. Available upon request.

two groups: firms above the sector median of the continuous measure of technology and firms below[31]. Results are exactly the same, there is not a significant impact of technology on supervisors' and core employees' pay. The penalization for managers remains.

The first step to solve this puzzle is to test the robustness of this result to the dropping of some variables from the initial specifications. After excluding the control for firm size, the negative coefficient attached to the technology index turns out to be no longer significant. At the same time, the coefficients attached to the technology index for supervisors considerable increase, even though they remain statistically insignificant[32]. Finally, the combined effect of simultaneously dropping human capital variables and the control for firm size from the core employees' equation leads to a significant positive impact of the technology index on earnings. In contrast, the non-significance of the coefficient remains unaltered if we drop human capital variables and firm size separately.

The interpretation we make of these results links firm size to the introduction of production technology. Doms *et al.* (1997) showed that firms which adopted advanced production technologies were already those paying higher wages and those which were the most productive ones before the adoption. According to their conclusion, no direct wage increases would directly stem from the adoption of production technologies, which is exactly the outcome of our regressions. Furthermore, the fact that the coefficient associated with the technology index is significant after simultaneously dropping firm size and human capital for core employees suggests that this type of workers are the users of production technologies, which can be only implemented by larger firms. On top of that, workers

[31] Doms et al. (1997) suggest the utilization of a count variable. We had to discard this alternative measure given the marked differences in terms of types of technology between the manufacture and the service sectors.
[32] However, we must note that the z-statistic also grows being larger than 1.2.

hired by larger firms are more qualified than workers in smaller firms. This human capital makes it possible to successfully adopt advanced production technologies.

The negative coefficient attached to the technology index for managers remains unanswered. It is difficult to find a plausible explanation for the strong negative impact of production technologies on managers' wages, since results only allow us nothing to tentatively venture hypotheses. In next section we will explore whether generic competences have any influence on this negative coefficient.

It is also interesting to highlight the results for the rest of the control variables, which fundamentally conform to results obtained in previous research. As expected, women are strongly penalized in the Catalan labour market. Although differences are not large, the gap slightly narrows for supervisors in comparison with core employees, and in turn, it more visibly narrows for managers. Not surprisingly, managers from Western countries are better paid than Spanish managers. The absence of penalization to workers originating from non-western countries is at least striking. This result should be explainable on the grounds that they are hired for worse jobs as compared with Spanish workers. However, all the same, they would receive the same pay as a Spanish worker in the same workplace. Core employees and supervisors working longer than 40 hours per week are conferred a considerable wage advantage. Alternatively, core employees working part-time[33] and those with temporary contracts are considerably worse paid.

[33] We consider as part-time workers those working less than 30 hour per week.

Table 8. Hedonic wage equations. Returns to Managers

	MODEL 1		MODEL 2		MODEL 3	
Problem-solving	-0.0131	(0.0206)	-0.0269	(0.0206)	-0.0286	(0.0208)
Client communication	0.0767***	(0.0185)	0.0705***	(0.018)	0.0719***	(0.0182)
High-level communication	0.0346	(0.0238)	0.0139	(0.0241)	0.0169	(0.024)
Planning skills	0.005	(0.0227)	-0.0076	(0.0229)	-0.0059	(0.0231)
Horizontal communication	0.0404	(0.0257)	0.0254	(0.0259)	0.0191	(0.0271)
Numeracy skills	0.0444**	(0.021)	0.0257	(0.0216)	0.0189	(0.0217)
Technical know-how	0.0103	(0.0274)	-0.0018	(0.0268)	-0.0009	(0.0266)
Literacy skills	-0.0668***	(0.0221)	-0.0627***	(0.0216)	-0.0631***	(0.0217)
Computer use	0.0185	(0.0289)	0.0207	(0.0282)	0.0119	(0.0285)
Female	-0.1764***	(0.0409)	-0.175***	(0.0401)	-0.1641***	(0.0411)
Western European	0.2476***	(0.0908)	0.2107**	(0.0974)	0.2099**	(0.0944)
Other countries	-0.2272	(0.2275)	-0.2557	(0.2297)	-0.2782	(0.2414)
Education level 2	0.1064*	(0.0565)	0.0912	(0.056)	0.0982*	(0.0555)
Education level 3	0.2397***	(0.0555)	0.2323***	(0.0548)	0.2388***	(0.054)
Education level 4	0.3741***	(0.0595)	0.3551***	(0.058)	0.3625***	(0.0575)
Experience	0.0288***	(0.0073)	0.0288***	(0.0073)	0.029***	(0.0073)
$Experience^2$	-0.0003*	(0.0001)	-0.0003*	(0.0001)	-0.0003*	(0.0001)
Tenure	0.0178***	(0.0045)	0.0163***	(0.0045)	0.0169***	(0.0044)
$Tenure^2$	-0.0005***	(0.0001)	-0.0005***	(0.0001)	-0.0005***	(0.0001)
MBA	0.124***	(0.0462)	0.0993**	(0.0446)	0.1018**	(0.0439)
Barcelona Metropolitan Area	0.0466	(0.03)	0.0528*	(0.0297)	0.0499*	(0.0297)
Size	0.0845***	(0.0186)	0.0827***	(0.0187)	0.0851***	(0.0186)
Part of a group	0.0049	(0.0411)	0.0084	(0.0408)	0.0087	(0.0403)
% exports	0.0297	(0.0714)	0.0727	(0.0715)	0.0813	(0.0716)
Technology Index	-0.057**	(0.0272)	-0.0469*	(0.0271)	-0.0481*	(0.027)
Temporary contract	0.0827	(0.0755)	0.0748	(0.0735)	0.0825	(0.0733)
< 30 hours/week	-0.116**	(0.0591)	-0.0898	(0.0572)	-0.0936	(0.0583)
> 40 hours/week	0.0469	(0.0306)	0.0476	(0.0301)	0.0493*	(0.0296)
Intensity			0.013	(0.0173)	0.013	(0.0178)
Degree of freedom			0.0862***	(0.0219)	0.0715***	(0.023)
Initiative					0.0375*	(0.0194)
Exchanging ideas					-0.0065	(0.021)
Non-basic computer use					0.0445	(0.0297)
Constant	6.6143***	(0.1181)	6.6477***	(0.1169)	6.6029***	(0.1184)
St. error of est./Log likelihood	0.2900	-796.4783	0.2841	-787.7807	0.2825	-785.2974
Chi^2 / Probability	301.33	0.00	297.10	0.00	317.7	0.00
McKelvey & Zavoina's R^2	0.252		0.269		0.274	

N = 569

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

Although not shown in the table, the model also includes 8 sector dummies.

Referential variables appear in Table I of the Appendix

Table 9. Hedonic wage equations. Returns to Supervisors

	MODEL 1		MODEL 2		MODEL 3	
Problem-solving	0.0053	(0.0154)	0.0023	(0.016)	0.0062	(0.0159)
Client communication	0.0297**	(0.0126)	0.0262**	(0.0129)	0.0289**	(0.0127)
High-level communication	0.026	(0.0179)	0.0189	(0.0186)	0.0219	(0.0184)
Planning skills	-0.0139	(0.0172)	-0.0176	(0.0173)	-0.0145	(0.0175)
Horizontal communication	0.007	(0.0163)	0.0039	(0.0163)	0.0131	(0.0166)
Numeracy skills	0.0332**	(0.0131)	0.0309**	(0.0132)	0.0296**	(0.0131)
Technical know-how	0.0028	(0.0191)	0.0003	(0.0191)	0.0021	(0.0193)
Literacy skills	0.0287	(0.0177)	0.0288	(0.0176)	0.0307*	(0.0173)
Computer use	-0.0175	(0.0145)	-0.02	(0.0146)	-0.0234	(0.0147)
Female	-0.1774***	(0.025)	-0.1779***	(0.0248)	-0.1757***	(0.0249)
Western European	-0.0914	(0.1575)	-0.0996	(0.1592)	-0.1289	(0.1513)
Other countries	-0.0396	(0.0805)	-0.0435	(0.0782)	-0.0497	(0.0785)
Education level 2	0.08***	(0.0247)	0.0754***	(0.0249)	0.0732***	(0.0246)
Education level 3	0.1546***	(0.0325)	0.1505***	(0.0326)	0.1526***	(0.0323)
Education level 4	0.2376***	(0.0414)	0.2388***	(0.0413)	0.2423***	(0.0415)
Experience	0.0155***	(0.0041)	0.0152***	(0.0041)	0.0156***	(0.0041)
Experience^2	-0.0001*	(0.0001)	-0.0001*	(0.0001)	-0.0001*	(0.0001)
Tenure	0.0038	(0.0034)	0.0041	(0.0035)	0.0042	(0.0034)
Tenure^2	-0.0001	(0.0001)	-0.0001	(0.0001)	-0.0001	(0.0001)
Training	-0.0143	(0.0219)	-0.0145	(0.0218)	-0.015	(0.0218)
Barcelona Metropolitan Area	0.0578***	(0.022)	0.062***	(0.022)	0.0651***	(0.0219)
Size	0.0724***	(0.0116)	0.0731***	(0.0116)	0.0747***	(0.0116)
Part of a group	-0.0199	(0.0275)	-0.0201	(0.0275)	-0.0152	(0.0275)
% exports	0.0646	(0.0525)	0.0763	(0.0526)	0.0867	(0.053)
Technology Index	0.0059	(0.0205)	0.004	(0.0209)	0.0036	(0.0209)
Temporary contract	-0.0333	(0.0377)	-0.0288	(0.0378)	-0.0185	(0.0375)
< 30 hours/week	-0.0392	(0.0449)	-0.04	(0.044)	-0.0404	(0.0445)
> 40 hours/week	0.0933***	(0.0236)	0.0944***	(0.0236)	0.0945***	(0.0234)
Intensity			-0.0013	(0.0132)	0.0018	(0.0131)
Degree of freedom			0.0305*	(0.0157)	0.0288*	(0.0165)
Initiative					0.0114	(0.0145)
Exchanging ideas					-0.0286*	(0.0152)
Non basic computer use					0.0406*	(0.0212)
Constant	6.7146***	(0.0686)	6.7268***	(0.0697)	6.6894***	(0.0728)
St. error of est./Log likelihood	0.2208	-949.3212	0.2199	-947.2907	0.2183	-943.4894
Chi^2 / Probability	465.17	0.00	463.27	0.00	485.2	0.00
McKelvey & Zavoina's R^2	0.355		0.360		0.368	

N = 607

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

Although not shown in the table, the model also includes 8 sector dummies.

Referential variables appear in Table II of the Appendix

Table 10. Hedonic wage equations. Returns to Core Employees

	MODEL 1		MODEL 2	
Problem-solving	0.0027	(0.0044)	-0.0001	(0.0045)
Client communication	0.0068	(0.0056)	0.0057	(0.0056)
High-level communication	0.0291***	(0.006)	0.0269***	(0.006)
Planning skills	0.0177***	(0.0047)	0.0136***	(0.005)
Horizontal communication	-0.0081	(0.0055)	-0.0101*	(0.0055)
Numeracy skills	0.0286***	(0.0062)	0.0267***	(0.0062)
Technical know-how	0	(0.0068)	-0.0015	(0.0067)
Literacy skills	0.0033	(0.0076)	0.0036	(0.0075)
Computer use	0.0009	(0.0055)	0.0009	(0.0055)
Female	-0.1761***	(0.0109)	-0.1782***	(0.0109)
Western European	0.0585	(0.0683)	0.0594	(0.0676)
Other countries	0.0178	(0.0228)	0.0163	(0.0227)
Education level 2	0.0765***	(0.0112)	0.0742***	(0.0113)
Education level 3	0.1726***	(0.0154)	0.1691***	(0.0155)
Education level 4	0.2642***	(0.0308)	0.2585***	(0.0308)
Experience	0.0124***	(0.0017)	0.0123***	(0.0017)
$Experience^2$	-0.0002***	(0)	-0.0002***	(0)
Tenure	0.0098***	(0.0017)	0.0097***	(0.0017)
$Tenure^2$	-0.0002***	(0)	-0.0001***	(0)
Training	0.0376***	(0.0092)	0.0373***	(0.0092)
Barcelona Metropolitan Area	0.0476***	(0.0093)	0.048***	(0.0093)
Size	-0.0016	(0.0051)	-0.0011	(0.0051)
Part of a group	0.0086	(0.014)	0.0077	(0.0139)
% exports	0.0901***	(0.0235)	0.0893***	(0.0234)
Technology Index	0.0046	(0.0083)	0.0049	(0.0082)
Temporary contract	-0.0714***	(0.015)	-0.0693***	(0.015)
< 30 hours/week	-0.1563***	(0.0187)	-0.1566***	(0.0187)
> 40 hours/week	0.0689***	(0.0151)	0.0652***	(0.0151)
Intensity			0.0057	(0.0046)
Degree of freedom			0.0129***	(0.0046)
Constant	6.6907***	(0.0285)	6.6915***	(0.0285)
St. error of est./Log likelihood	0.2211	-3930.1929	0.2207	-3925.3169
Chi^2 / Probability	1659.47	0.00	1689.37	0.00
McKelvey & Zavoina's R^2	0.352		0.354	

N=3095
Robust standard errors in parentheses; * denotes significant at 10%; ** denotes significant at 5%; *** denotes significant at 1%
Although not shown in the table, the model also includes 8 sector dummies.
Referential variables appear in Table II of the Appendix

6. The pay-off to generic competences in technological firms

According to the evidence obtained in the previous section, working in a more technologically advanced firm does not confer a direct positive pay-off. What is worse, managers are penalized. These findings should not exclude indirect effects, nevertheless. That is, the returns to human capital could be higher, or even lower, for those workers in firms using more advanced technologies. In this section we now address whether there are differences in the pay-off to generic competences depending on the degree of technology adopted by the firm. We reestimate the full models in the precedent section adding an interaction between the utilization of one of the generic competences and a dummy variable that takes value one if the firm is above the median use of technology in its sector[34]. The sector median establishes the difference between high-tech firms and low-tech firms.

Table 11. Returns to each of the generic competences and its interaction with the type of firm.

	Managers		Supervisors		Core employees	
Problem-solving	-0.0441	(0.0281)	0.0113	(0.0203)	-0.0046	(0.0056)
Problem.- solving x technology	0.0263	(0.0373)	-0.0125	(0.0318)	0.0115	(0.0088)
Client communication	0.1001***	(0.0231)	0.0213	(0.0168)	0.0012	(0.0071)
Client com. x technology	-0.058*	(0.0334)	0.0165	(0.0229)	0.0097	(0.0102)
High-level communication	0.0266	(0.031)	0.0038	(0.0233)	0.0251***	(0.0077)
High-level com. x technology	-0.0132	(0.04)	0.044	(0.0326)	0.0042	(0.0117)
Planning skills	0.0061	(0.0287)	-0.0027	(0.0215)	0.0135**	(0.0062)
Planning skills x technology	-0.0352	(0.0463)	-0.0304	(0.0342)	0.0002	(0.0092)
Horizontal communication	0.0167	(0.0365)	0.0359*	(0.0218)	-0.0117*	(0.0069)
Horizontal com x technology	-0.0013	(0.0474)	-0.052*	(0.0313)	0.004	(0.0106)
Numeracy skills	-0.0205	(0.0314)	0.0333*	(0.0174)	0.0282***	(0.0077)
Numeracy skills x technology	0.0692*	(0.0388)	-0.0078	(0.0233)	-0.0034	(0.011)
Technical know-how	-0.0556	(0.0369)	-0.0109	(0.0256)	0.0117	(0.0085)
Tech. know-how x technology	0.1104**	(0.0491)	0.0296	(0.0364)	-0.0298**	(0.0124)
Literacy skills	-0.066**	(0.0294)	0.0484**	(0.0231)	-0.0003	(0.0093)
Literacy skills x technology	0.0117	(0.0424)	-0.0413	(0.0309)	0.0094	(0.0146)
Computer use	-0.0116	(0.0349)	-0.0211	(0.0183)	0.0003	(0.0066)
Computer use x technology	0.0585	(0.0493)	-0.0053	(0.0239)	0.0013	(0.0085)

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

[34] We have replaced the continuous technological variable by this dummy variable, as it makes the interpretation more straight forward.

Instead of introducing all the interactions simultaneously, we estimate 9 models (one for each of the generic competences), and each of them 3 times covering the three possible positions. Table 11 only presents the returns to each of the generic competences and the impact of the interaction on pay[35]. We do not include the coefficient attached to the type of firm (high- or low-tech) because the non significance of its coefficient prevails irrespective of the position in the firm or the competence introduced. We must note that the inclusion of interactions makes the previously negative impact of technology on managers' wages no longer significant. It could be that being the utilization of generic competences equal to the mean for each of the three positions, the direct effect of technology is null.

In the previous section we found that the utilization of client communication and number skills conferred considerable gains to managers. According to this table, the premium for client communication skills is reduced in high-tech firms, while number skills are only rewarded in this type of firms. Technical know-how, which was not remunerated in table 8, carries a remarkable pay-off when the firm is above the median production technology. The positive impact of client communication skills on supervisors' earnings has vanished. In contrast, a premium to literacy skills for both high-tech and low-tech supervisors emerges. Interestingly, there is a positive impact of horizontal communication skills in low-tech firms which is swept out in more technologically advanced firms. Finally, number skills are equally rewarded in high-tech and low-tech firms. In the case of core employees, the only and interesting remark is related to the surprising penalization to the acquisition of technical know-how in more technologically advanced firms. It is noteworthy that problem-solving skills and computer use are equally unremunerative in both high- and low-tech firms which the rank in the firm.

[35] Since the technological dummy takes value 0 when the continuous variable from which it is derived is below the median in its sector., the table shows the returns to generic competences for below the median firms

Table 11 reveals that the pay-off to some of the generic competences is sensitive to the type of technology implemented by the firm. On the one hand, more technology can result in a lower pay-off, particularly for those competences that are related to communication skills. An hypothesis could be that the contribution of these types of competences to workers' productivity is reduced by the introduction of technologies in the production process. On the other hand, the opposite occurs with technical knowledge and number skills. Undoubtedly, the utilization of these skills should function as a complement of technology that fosters workers' productivity. Hence, it is possible to distinguish two types of generic competences, those the contribution of which to workers' productivity increases with the adoption of production technologies and those which lead to the opposite effect. The former are related to technical generic competences for which cognitive ability is essential, whereas the latter are more associated with activities for which non-cognitive skills are more important. The adoption of production technologies can impinge on the contribution of this sort of competences on workers' productivity.

The varying returns to generic competences primarily take place for managers, whereas in the case of supervisors and core employees the implications of the introduction of the interaction in the wage equations are minor. It implies that managers' productivity is more sensitive to the level technology that the firm uses. In fact, it was the managers' specification the only that yielded a significant and negative impact on pay. We interpret that direct penalization on earnings as the reduction of the large premium to the utilization of client communication skills. In other words, managers in high-tech firms are not as rewarded as managers in low-tech firms for their client communications skills. The non inclusion of the interactions in the wage equation resulted in a striking reduction of managers' pay in high-tech firms.

8. Conclusions

In this paper we have examined the role of generic competences in the determination of earnings for managers, supervisors and core employees in Catalan firms. A specially designed matched employer-employee data set has enabled us to mitigate part of the estimation problems in previous research. First, departing from the self-evaluation of the content of the job in terms of 26 competences, we have been able to derive a structure of 9 generic competences which allows comparability with previous papers: problem-solving skills, client communication, planning skills, high-level communication, horizontal communication, numeracy skills, technical know-how, literacy skills and computer use. Second, the wide information provided within the survey allows a more suitable control for individuals', firms, and job characteristics, which in turn helps to attenuate the impact of biases on the estimates.

The results of the hedonic wage equations show that the pay-off to generic competences differs depending on the position of the worker in the firm. Only number skills conferred a significant positive pay-off to all workers, irregardless of their rank. This result gives support to previous findings that highlighted the importance of cognitive skills. On top of that, client communication skills carried a significant positive premium for managers, again client communication skills in addition to literacy skills for supervisors, and high-level communication skills in addition to planning skills for core employees. It stands out that computer use by itself does not pay off. Finally, we have not found a direct positive impact of production technology on workers' pay. This result is consistent with the fact that Doms *et al.* (1997) found that firms which had implemented advanced production technologies had been paying higher wages prior to its adoption.

Finally, by means of interactions, we have tested the sensitivity of the pay-offs to generic competences to the level of technology. We have discovered that this sensitivity is more notorious for managers. On the one hand, the large returns to client communication skills considerably diminish in high-tech firms. This could account for the strong negative impact of technology on managers' pay. On the other hand, number skills and technical know-how are better paid in high-tech firms. This establishes a frontier between two types of generic competences. The first type is more related to cognitive abilities which aid the worker to deal with technical activities that are necessary complements of technology. In opposition to the first type, the second type deals with non-technical activities in which non-cognitive abilities are more important.

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Appendix I

Table I: Descriptive Statistics

Dependent variable: earnings

Managers		Supervisors		Core employees	
Interval	**%**	**Interval**	**%**	**Interval**	**%**
0-2000€	31.99%	0-1000€	4.12%	0-700 €	4.39%
2001-2600€	27.77%	1001-1300€	25.04%	701-1000€	33.28%
2601-3200€	19.86%	1301-1600€	25.54%	1001-1300€	36.96%
3201-3800€	10.19%	1601-1900€	20.26%	1301-1600€	15.54%
3801-4400€	5.10%	1901-2200€	12.03%	1601-1900€	6.69%
4601-5200€	2.46%	2201-2500€	8.07%	1901-2200€	1.94%
5201-5800€	1.05%	2501-2800€	3.13%	2201-2500€	0.71%
>5800€	1.58%	> 2800€	1.81%	> 2500€	0.48%

Independent variables

	Total Sample			Managers			Supervisors			Core employees		
	N	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**
Problem-solving	4271	0.00	0.92	569	0.00	0.74	607	0.19	0.64	3095	-0.04	1.00
Client communication	4271	0.00	0.86	569	0.28	0.79	607	-0.02	0.82	3095	-0.05	0.87
High-level communication	4271	0.00	0.84	569	0.64	0.64	607	0.71	0.59	3095	-0.26	0.77
Planning skills	4271	0.00	0.83	569	0.16	0.57	607	0.20	0.56	3095	-0.07	0.90
Horizontal communication	4271	0.00	0.79	569	0.00	0.59	607	0.05	0.62	3095	-0.01	0.85
Numeracy skills	4271	0.00	0.81	569	0.34	0.71	607	0.08	0.79	3095	-0.08	0.81
Technical know-how	4271	0.00	0.70	569	0.16	0.54	607	0.09	0.58	3095	-0.05	0.74
Literacy skills	4271	0.00	0.62	569	0.23	0.64	607	0.04	0.62	3095	-0.05	0.61
Computer intensity	4271	0.00	1.00	569	0.58	0.58	607	0.30	0.82	3095	-0.17	1.04
Basic use of computers [b]	1176	0.62		569	0.50		607	0.72				
Non basic use of computers	1176	0.38		569	0.50		607	0.28				
Intensity	4271	0.00	1.00	569	0.26	0.84	607	0.20	0.85	3095	-0.09	1.04
Freedom to organize[c]	3095	0.00	1.00							3095	0.00	1.00
Freedom to organize[c]	1176	0.00	0.72	569	0.18	0.70	607	-0.17	0.69			
Initiative	1176	0.00	0.76	569	0.11	0.71	607	-0.11	0.79			
Exchanging ideas	1176	0.00	0.77	569	0.03	0.76	607	-0.03	0.78			
Productivity: <1 months[d]	4271	0.09								3095	0.13	
Productivity: 1-3 months	4271	0.21		569	0.23		607	0.29		3095	0.19	
Productivity: 3-6 months	4271	0.17		569	0.29		607	0.20		3095	0.14	
Productivity: 1/2-1 year	4271	0.19		569	0.05		607	0.09		3095	0.23	
Productivity: 1-2 years	4271	0.18		569	0.12		607	0.18		3095	0.19	
Productivity: >2 years	4271	0.16		569	0.31		607	0.23		3095	0.12	
Female	4271	0.31		569	0.21		607	0.28		3095	0.34	
Spanish[a]	4271	0.96		569	0.98		607	0.99		3095	0.95	
Western Europe	4271	0.01		569	0.02		607	0.01		3095	0.01	
Other countries	4271	0.04		569	0.01		607	0.01		3095	0.05	
Education Level 1[a]	4271	0.47		569	0.10		607	0.37		3095	0.56	
Education Level 2	4271	0.25		569	0.24		607	0.29		3095	0.25	
Education Level 3	4271	0.19		569	0.32		607	0.23		3095	0.15	
Education Level 4	4271	0.09		569	0.33		607	0.11		3095	0.04	
Experience	4271	19.86	10.97	569	21.64	9.77	607	22.13	10.68	3095	19.09	11.13
$Experience^2$	4271	514.7	498.1	569	563.5	466.9	607	603.6	512.8	3095	488.2	498.2
Tenure	4271	9.18	8.85	569	11.47	8.84	607	11.71	9.27	3095	8.27	8.59
$Tenure^2$	4271	162.6	291.3	569	209.6	293.8	607	222.9	333.3	3095	142.1	279.2
MBA	569	0.09		569	0.09							
Training	3702	0.67					607	0.73		3095	0.66	
Temporary contract	4271	0.12		569	0.05		607	0.05		3095	0.15	
Hours worked<35	4271	0.09		569	0.07		607	0.07		3095	0.09	
Hours worked<40 [a]	4271	0.77		569	0.59		607	0.70		3095	0.81	
Hours worked>40	4271	0.15		569	0.34		607	0.22		3095	0.09	
Food industry	4271	0.12		569	0.13		607	0.12		3095	0.12	
Electronics	4271	0.09		569	0.13		607	0.08		3095	0.09	
Hotel industry	4271	0.08		569	0.05		607	0.10		3095	0.07	
Computer equipment	4271	0.10		569	0.14		607	0.06		3095	0.09	
Health	4271	0.12		569	0.10		607	0.13		3095	0.12	
Rubber and plastic materials	4271	0.08		569	0.08		607	0.12		3095	0.07	
Metal products	4271	0.20		569	0.17		607	0.17		3095	0.21	
Machinery and equipment	4271	0.17		569	0.15		607	0.16		3095	0.17	
Furniture.	4271	0.05		569	0.05		607	0.06		3095	0.05	
Barcelona Metropolitan Area	4271	0.58		569	0.60		607	0.60		3095	0.57	
Log number of workers	4271	3.55	0.99	569	3.65	0.95	607	3.63	0.98	3095	3.51	1.00
Part of a group	4271	0.14		569	0.15		607	0.18		3095	0.14	
% Exports	4271	0.16	0.22	569	0.18	0.22	607	0.17	0.22	3095	0.16	0.21
Technology Index	4271	0.09	0.28	569	0.13	0.29	607	0.06	0.28	3095	0.09	0.28

Notes: Means reflect percentages in dummy variables. No standard deviations for dummy variables are shown.
[a] Referential variables in the regressions.
[b] The referential group for managers is the addition of Level 1 and Level 2 of computer complexity.
[c] This variables is computed in different ways depending on the position within the firms.
[d] This group is only included in the core employees interview.

Appendix II

Technology Index

General Managers had to indicate which of a set of production technologies had been implemented by their firms. Given the logical differences between sectors, questionnaires were adapted to the most common production technologies in each of them, especially for the service industry. As a result, the set of production technologies are common for all manufacturing firms, whereas there is a specific set for each of the sectors within the service industry[36]. Given the differences between sectors, a problem of comparability between firms arises. We solve this problem by constructing a continuous measure, which is used in the estimations presented in tables 8, 9 and 10. This measure reflects the situation of each of the firms related to the rest of the firms in the same sector.

[36] The set of 8 production technologies considered for manufacturing firms were Automatic sensors for controlling inputs and outputs; Warehouse management automatic 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. In the hotel industry General Managers were asked which software was being used. The options were standard software (Spreadsheet, Text processors); standard software modified to meet firm's needs; hotel sector specific standard software; hotel sector specific standard software modified to meet firm's needs; software developed by the branch; software developed by the hotel. Additionally, they were asked whether they had a web page which enabled customers to book on-line. General Managers in the computer sector where asked which of the following software they were using: MVS; OS 400; Linux; Unix; Windows NT, Windows XP or Windows Server 2003; Windows 95/98, Windows ME; MS DOS; other software. Besides, they were also asked about the programming language they were using: Oriented to objects (C++, Java, J2SE, J2EE, J2ME, C# Smalltalk, Eiffel, .NET); Web programming (PHP, ASP, ASP.NET, ColdFusion, JSP, Servlet); Visual programming (Visual Basic, Visual Basic.NET, Delphi (Object Pascal)); Procedural programming (C, BASIC, Pascal, Fortran, Clipper, PL/1, SNOBOL, COBOL, RPG); Script language (tcl, Bash, sh, Javascript, VBScript, ActionScript, Max Script); Label language (HTML, CSS, XML, WAP, XHTML); Data management (SQL, MySQL, dBase, Visual FoxPro) and other. The set of technologies considered in the health sector included Linear Accelerator; Digital Angiograph; Endoscopic Capsule; Robotic Surgery; Bone Densitometer; ECMO; Ecographer; Gamma Camera; Laser; Mamographer; PET; Magnetic Resonance; DNA Sequencer; Telemedicine System/PACS; TAC Multicut; other.