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ARTICLE

Using the job requirements approach and matched employer-employee data to investigate the content of individuals' human capital

Ferran Mane[1] · **Daniel Miravet**[2]

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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 tasks 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. This paper gives evidence that the returns to generic skills differ depending on the position of the worker in the firm. Only numeracy skills are reward independent of the occupational status of the worker. We also show that generic skills and other measures of human capital have independent effects on wages.

JEL Classification J24 · J31

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✉ Ferran Mane
ferran.mane@urv.cat

✉ Daniel Miravet
daniel.miravet@urv.cat

[1] Department of Economics and CREIP, Universitat Rovira i Virgili, Av. Universitat 1, 43204 Reus, Catalonia, Spain

[2] Department of Economics, Universitat Rovira i Virgili, Av. Universitat 1, 43204 Reus, Catalonia, Spain

Messung von individuellem Humankapital auf Basis des „Jobanforderungsansatzes" (job requirements approach) und zusammengespielter Arbeitgeber-Arbeitnehmer-Daten

Zusammenfassung Ziel dieses Beitrags ist es, die Erträge aus Humankapital zu messen. Wir nutzen hierzu einen einzigartigen Datensatz, der aus zusammengespielten Informationen von Betrieben und Beschäftigten (matched employer-employee data) besteht. Die Daten zum individuellen Humankapital beinhalten ein Set von 26 Aufgaben (tasks), die sehr detailliert erfassen, wie Beschäftigte ihre Fähigkeiten (skills) einsetzen. Damit können wir das Humankapitalkonzept erweitern und die Art der Fähigkeiten diskutieren, die mit einer höheren Produktivität am Arbeitsplatz verbunden sind – und damit auch einen höheren Ertrag je Beschäftigtem. Der Beitrag liefert empirische Evidenz dafür, dass die Erträge, die aus allgemeinen Fähigkeiten resultieren, von der jeweiligen Position des Beschäftigten in der Firma abhängen. Lediglich bei rechnerischen Fähigkeiten ist der Ertrag unabhängig von der beruflichen Position des Beschäftigten. Zudem zeigen wir, dass allgemeine Fähigkeiten und andere Aspekte von Humankapital einen eigenständigen Effekt auf das Lohnniveau haben.

1 Introduction

It is widely accepted that wages depend, in part, on the individual's productive skills. Very often, researchers have used as a proxy for these skills measures of educational level and labour market experience (and tenure). Even though there exists a vast literature on the returns to education and experience that clearly shows a positive payoff to both of them, there has always been some sort of discomfort with the precise content of such indicators or, in other words, with equating workers' skills to the workers' educational level. The obvious problem is that education (or schooling) and experience are investment measures and, therefore, can only provide very general insights on issues like what factors determine the skills that employers demand, why these skills are required or how these skills requirements change over time.

To a large extent the use of schooling and experience data can be justified on the grounds of practicality: it was the only type of data available in large scale surveys and over time. Fortunately, this is changing thanks to the availability of new data sets such as, among others, the Skill Survey in the UK, the CHEERS and REFLEX projectsor the new OCDE data set from the PIAAC survey. At the same time, some serious theoretical discussion is being developed under the rubric of the "task approach" to analyze job skill requirements (Autor et al. 2003; Autor and Handel 2013). Pouliakas and Russo (2015) discuss that the crux of the task framework is that the core activities that workers undertake in their jobs are linked to the skills required by workers to carry out these tasks. The task approach potentially offers a microfundation for linking the aggregate demand for skills in the labour market to the specific skills demands of given job activities (Autor and Handel 2013:60).

In this paper we aim to add some empirical evidence to the growing literature in this area. Specifically, we will initially discuss how job tasks requirements are related to technological, product innovation and work organization characteristics of the firm. We then will estimate, as has been a tradition in this literature, a Mincer wage equation but with the inclusion of the measures of generic skills characteristics of the job. Thus, we will be able to determine the value of each of these generic skills, and discuss which of them make the worker more productive. We also want to discuss more directly what happen to the respective coefficients when both types of variables, traditional human capital variables and skills, are included in the equation estimated.

The man contributions of this paper are related to the use of a unique employer-employee data set which offers wide and detailed information on firms, workers and workplace characteristics. The characteristics of the data set help to address the problem of using information on job characteristics at the level of occupations instead of information at the individual worker level. In addition, most papers do not have the appropriate data to relate job skill requirements to the technological and human resource practices specific context. Our data will allow us to discuss them.

The paper is laid out as follows. In the next section we review the literature addressing the returns to skills and the determinants of generic skills. In Sect. 2 we describe the survey we draw our data from and develop the indices that measure the utilization of generic skills. In Sect. 3 we present our empirical analysis. A brief conclusions section summarizes the main results.

2 Previous research

2.1 From education to skill measures

Economists have traditionally related earnings differences to differences in human capital. The logic is that individuals (and countries) with higher level of human capital are more productive and hence receive larger compensation. But what is human capital? How human capital should be measured? A large body of research has proxied it using years of schooling and experience, mainly due to the relatively abundant data on these measures[1]. However, as thoroughly discussed in Hanushek and Woessmann (2008) and Hanushek (2014), it is quite clear that school attainment and experience are proxies for the skills that actually contribute to productivity and, therefore, it is necessary to accurately measure the skills that a given amount of education or training produces. In recent years, through different data sources, it has become possible to directly measure the skills possessed by individuals. Suleman and Paul (2006) distinguish two streams of research broadly classified depending on the typology of data used. The first one uses information on cognitive and non-cognitive skills measured by means of scholar or psychological tests providing comparable scores. A second line of research uses subjective measures of the utilization of skills by directly asking employees or employers.

There is a well-established empirical evidence that cognitive skills, mainly literacy and numeracy, carry on sizably positive effects on labour market outcomes (Hanushek et al. 2015). Early papers used longitudinal surveys mostly from the US (Murnane et al. 1995, 2000; Tyler et al. 1999; Tyler 2004) and, to a lesser extent, similar data on the UK (McIntosh and Vignoles 2001; Dearden et al. 2002; Grinyer 2005; Vignoles et al. 2011). Apart from the direct impact on the productive capacity of the individual, it is claimed that there also is an indirect effect as cognitive skills increase the likelihood of acquiring higher levels of education, which in turn leads to higher economic returns (Cunha et al. 2006)[2]. A more recent body of research within this group of cognitive skills analysis has used international data sets,

[1] See Psacharopoulos and Patrinos (2004) and Monteneground Patrinos (2014) for reviews of the extended literature on returns to education.

[2] Though it has also been proved that schooling affects individuals' cognitive skills (Carlsson et al. 2015).

mainly the International Adult Literacy Survey (IALS)[3] and lately the Programme for the International Assessment of Adult Competences (PIACC). Using IALS and basically estimating a skill-augmented mincerian equation, a number of papers (Denny et al. 2003; Green and Riddell 2003, 2015; Leuven et al. 2004; Hanushek and Zhang 2009; Van de Werfhorst 2011; Barone and Van de Werfhorst 2011) show that the estimated return to formal education is sensitive to the inclusion of cognitive skill measures, though in general education has a stronger effect than cognitive skills. In almost all countries, the test scores have a well-determined effect on earnings although there is considerable variation in the size of the effect. These findings of a positive and independent effect of cognitive skills are reproduced in papers using the new PIACC data set, claimed to be of better quality than IALS (Broecke 2015; Cappellari et al. 2015; Hanushek et al. 2015; Holzer and Lerman 2015; Paccagnella 2014; Pouliakas and Russo 2015). With respect the impact of non-cognitive skills (a broad category encompassing personality, socioemotional and behaviors), there is growing evidence that they are also very important for labour market outcomes. The empirical literature shows a strong and robust relationship between certain non-cognitive skills, such as dependability, persistence and docility and labour market outcomes (Cunha et al. 2010) with the claim that for many outcomes, their predictive power rivals or exceeds that of cognitive skills (Kautz et al. 2015).

A second line of research, not yet as prolific as the one we just described, can be labeled under the rubric of "task based analysis" (Handel 2008; Rohrbach-Schmidt and Tiemann 2013). In most cases the data is collected using the "job requirements approach", essentially an adaptation of occupational psychologists' methods in the context of a socioeconomic survey (Green 2012). The idea is to collect information on the tasks that are being done in jobs and group them into domains that correspond to a common typology of skills domains. The main focus of attention is on generic skills (viewed as the managerial, intra-personal, communication and interpersonal skills that are used to resolve workplace problems, for instance critical thinking, problem-solving, team-working or leadership skills) and data is collected at the individual worker level. The main two sources of information come from the UK's Skill Surveys and the Qualification and Career Surveys in Germany[4]. The recent PIACC survey also contains modules enquiring about the frequency of use of several tasks which will open up opportunities for further research (Pouliakas and Russo 2015). The positive impact of generic skills on wages seems well documented (Green 1998, 2012; Heijke et al.2003; Dickerson and Green 2004; Garcia Aracil et al. 2004; Johnes 2005; Suleman and Paul 2007; Mane and Miravet 2010; Autor and Handel 2013; Leoni et al. 2015). Autor and Handel (2013) show that the variance in analytical, routine and manual tasks carried out by US workers is a significant predictor of wage differences not only between occupations but also among workers in the same occupation. Some recent work using specially design data to analyze a specific type of skill provides robustness on these results (see for instance Patt (2015) or Ederer et al. [2015]). When data availability renders the exercise possible, it is showed that the importance of these skills has been growing over the last decades (Spitz-Oener 2006; Green 2012; Handel 2012). There is, however, a recognized problem of task classification into different skill domains (Autor et al. 2003; Green 2012). Rohrbach-Schmidt and Tiemann (2013) show for the case of Germany that different strategies for classifying tasks into tasks domainslead to different conclusions about task change. An additional issue relates to how best develop generic skills. Using data on Italian college graduates 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 payoff. However, academic competences played a supportive role to learn management competences. In a similar study but using a much larger data set and in a different institutional setting (Catalan graduates) Mane and Miravet (2010) come to a similar conclusion. They found that management skills, especially those learnt on-the-job, carried out the highest pay-off and that this learning was largely determined by the academic knowledge developed at college.

2.2 Technical change, organizational change and generic skills

In the past years we have observed how the use of new technologies has spread among firms with the aim to improve productivity. Although the existing evidence shows a positive relationship between new technologies and firm

[3] For information see https://nces.ed.gov/statprog/handbook/ials.asp. The Adult Literacy and Lifeskills Survey (ALL) was meant to represent a second round of the IALS project, but the launching of the OCDE's PIAAC project re-focus countries' interest. See https://nces.ed.gov/surveys/all/.

[4] There are some initiatives in other countries as the STAM survey in US (Handel 2008), the ISFOL database in Italy (Leoni and Gritti 2015) and in the context of some developing economies the STEP Skills Measurement Survey of the World Bank (Pierre et al. 2014). In a quite different context but collecting similar data, the CHEERS and REFLEX projects provide information for college graduates in different countries.

productivity, some recent studies point out that investment in new technologies is not enough to sustain improvements in productivity levels. In addition to new technologies firms also need to change their production process by implementing new forms of work organization, such as total quality circles, work teams, problem solving groups, or information sharing systems (Osterman 1994; Bresnahan et al. 2002; Black and Lynch 2004; Osterman 2006; Piva et al. 2005).

At the same time, as Cozzarin and Percival 2010 point out, although firms invest in new technologies or implement new organizational practices, unless employees make efficient use of these elements the firm will not see high levels of returns on their investments. The evidence suggests that only skilled workers can make a good use of these new technologies or take full advantage of the implementation of new work organizational practices. Bayo-Moriones et al. 2006 claim that investments in new technologies increases production process complexity, raising hence problem-solving demands while generating greater information flows. In order to cope with these changes, firms need to decentralize the decision-making process and flatten their hierarchy levels, which would make organisational structures based on teamwork, quality circles, or problem solving groups more appropriate. It is in this new competitive context, where technological change and organizational change take place that the requirements for more skilled workers increase. This is because more skilled workers have a greater ability to use new technologies, handle information, communicate and interact with other people, while tending to be more autonomous.

In addition to the impact of technological and organizational change on workers' skills, recent research shows that firms that adopt business strategies based on product market diversification, quality and innovation generate a higher demand for skills (Mason 2011; Green and Mason 2015).

As it carefully discussed in Green (2012), Leoni and Gritti (2015) and Pouliakas and Russo (2015) even though there is a broad consensus of the importance of human capital within the context of technological and organizational change, very little research exists to date that directly connects these changes to specific skill requirements at the individual worker level.

3 Data and variables

3.1 The Survey

The data set derives from a unique employer-employee survey of small-and-medium-size firms (10 to 250 employees) conducted between September 2005 and May 2006 in Catalonia, and jointly sponsored by the SMEs employers' association and the Catalan government. The survey took as a model the Canadian WES and the UK Skill Survey. Firms were randomly selected within 9 specific sectors of the economy: 6 manufacturing industries (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 service industries (hotels and restaurants, computer and related activities, and health and social work). The final sample consists of 499 firms (about 17 % of the universe). Representativeness of the sample at the industry level was checked and consistency confirmed.

The survey consists of four questionnaires: one for the CEO that incorporates firm level information and one for each of the key hierarchical levels in the firm (managers, supervisors, and core employees[5]) that comprises individual employee information. The questionnaire for CEOs asked for detailed 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, HR practices and work organization). 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, among others a list of tasks that could characterize their jobs. The final sample at the employee level contains 4,347 employees, 568 of whom are managers, 630 supervisors, and 3,149 core employees. Over all, these sample represents 60 % of the total number of targeted employees, with a similar distribution by occupational categories among firms.

3.2 Key variables: generic skills for Managers, Supervisors and Core Employees

Workers had to report to what extent their jobs involved a set of 26 tasks. They had to rate the importance of each of these activities on a 5-point scale ranging from "essential" (scored 5) to "not important at all" (scored 1). All items used the same scale. To facilitate the use of this information in our estimations, we applied factor analysis, as it is usual with this type of data (Green 2012), to explore how to reduce this large number of tasks into a smaller number of factors, considering the covariance of items in the data as well as theory. This process yielded eight fac-

[5] 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.

Table 1 Classification of skills emerging from factor analysis

Original list of tasks	Competences
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 Counseling, 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 (Basic and Advanced)
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 (Read and Write)

tors that were easily interpreted as indices for the following skills domains: problem solving, client communication, high-level communication, planning skills, horizontal communication, numeracy skills, technical knowledge and literacy skills. Table 1 details under each sub-heading the item upon which each factor loaded strongly (more details of the process can be found in Appendix A).

The eight skill domains emerging from factor analysis present a structure that is fundamentally consistent with the one obtained by Dickerson and Green (2004), with the difference that they had a further category, called checking skills, which appears in Table 1 as a part of problem solving.

Usually, after the exploratory analysis, factor scores are calculated and used as indices for further analysis. However, Green (2012:13) claims that simple average scores from the responses to the component items are more transparent indices and facilitates interpretation of the results. The problem is that these indices present a high level of correlation among them which difficult their joint use in, for instance, wage models. To account for both issues we generated two types of indices: a first one with the average scores and a second one using factor scores applying an orthogonal technique that creates factors uncorrelated among them[6]. We use either one depending on the type of analysis, but the results do not fundamentally change and it is just a matter of simplicity.

Also, we explored splitting the numeracy and literacy indices into two separate measures, one for each of their two components. It may be argued that they reflect very different levels of expertise. This is clearly the case for the numeracy index for which we created two variables named basic (calculations using decimals, percentages or fractions) and advanced (calculations using advanced mathematical or statistical procedures). For the literacy index it is not as much a matter of "level" as it is of different (though interrelated) type of skills, but we decided to also create two independent indices named writing and reading.

3.3 Key variables: firm level characteristics

One of the main advantages of our data set is the highly detailed information on firms' product/process strategies and a on their Human Resource policies. Our approach to the analysis of the determinants of the skill content of tasks is very preliminary and explorative and with the main goal of contextualizing the main discussion on the wage returns to skills. Therefore, we just created a few variables to basically capture some of the main issues discussed in the relevant literature. Specifically, we created the following measures:

- *Product innovation*: dummy variable with a value of 1 when the firm had introduced a new product over the last 2 years.
- *Product strategy*: dummy variable with a value of 1 when the firm claimed to have a commitment to a specific strategy of product innovation. The concept of product strategy was introduced in the questionnaire as "having a process, mostly formal, of the definition of the product and how it has to evolve over time".
- *Leadership in market*: dummy variable with a value of 1 when the main firm's product, defined as the one with the larger percentage over total firm's sells, is the product with the larger market share of the total product market.
- *Process innovation*: dummy variable with a value of 1 when the firm had introduced a major change in the production system over the last 2 years.
- *Technological intensity*: variable with a 1, 2 or 3 value reflecting the position of the firm (tercils) in an industry specific continuous normalized scale of the number of

[6] In addition, using this technique allows for comparability with other papers that have also used it: Green (1998), Dickerson and Green (2004), Johnes (2005) and Green et al. (2007).

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

	Gender		Highest educational level attained				Occupation		
	Men	Women	Educ. 1	Educ. 2	Educ. 3	Educ. 4	Manager	Supervisor	Core employee
All skills	0.011	–0.030	–0.266	0.061	0.338	0.520	0.648	0.537	–0.231
Prob. solv	0.033	–0.063	–0.098	0.079	0.109	0.087	0.185	0.336	–0.103
Client com	–0.026	0.057	–0.179	–0.020	0.264	0.419	0.498	0.197	–0.133
High com	0.053	–0.141	–0.220	0.008	0.246	0.616	0.854	0.811	–0.325
Planning	0.005	–0.010	–0.139	0.023	0.171	0.309	0.434	0.388	–0.160
Horiz. com	–0.026	0.057	–0.146	0.020	0.227	0.240	0.333	0.410	–0.146
Numeracy	0.075	–0.169	–0.173	0.082	0.169	0.324	0.496	0.275	–0.149
Basic	0.061	–0.133	–0.205	0.134	0.192	0.309	0.501	0.266	–0.148
Advanced	0.078	–0.179	–0.110	0.013	0.117	0.285	0.408	0.239	–0.125
Literacy	–0.023	0.035	–0.287	0.005	0.402	0.644	0.591	0.373	–0.187
Read	–0.040	0.072	–0.235	0.024	0.336	0.456	0.522	0.295	–0.158
Write	–0.000	–0.013	–0.276	–0.016	0.381	0.698	0.529	0.370	–0.175
Tec. know	0.011	–0.028	–0.295	0.109	0.370	0.476	0.450	0.335	–0.153
Computer	–0.055	0.124	–0.423	0.201	0.506	0.624	0.598	0.298	–0.173

Prob. solv. Problem-solving, *Client com.* Client communication, *High com.* High-level communication, *Horiz. com.* Horizontal communication, *Tec. know.* Technical know-how, *Educ. 1* No qualifications, Primary 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

technological elements (devices directly involved in the production proces) weighted by their complexity present in the firm. For each industry the questionnaire incorporated a specific list of devices ordered by complexity reflecting the idiosyncrasies of that industry.

- *Variable payment*: dummy variable with a value of 1 when the worker claims to have part of their wage being paid as a variable payment.
- *Centralization of decisions*: we introduced in the CEO questionnaire a list of eleven activities and ask who had the final word in organizing them allowing picking just one out of different possibilities: core employee, team of workers, supervisor, managers or CEO. The list of activities goes from daily and weekly organization of tasks to staffing, relation with suppliers, training, quality control or election of technologies. Using factor analysis we created two indices. The first one (*centralization of basic tasks*) loads mainly on how to organize the deployment of daily and weekly tasks in the workplace; while the second factor (*centralization of strategic decisions*) summarizes the rest of the activities that have more firm level and strategic implications. The scale of the variables implies that a high value reflects centralization of decisions (at the CEO level).
- *Work organization*: we also introduced in the questionnaire a question on whether it was formally used 8 different types of work organization practices, as information sharing, job rotation or quality circles. Again using factor analysis we developed two indices. The first one (*information sharing-teams*) basically relies on the use of employee suggestion program, information sharing with employees, self-directed work groups and solving problem teams; the second one (*job redesign*) basically loads on job rotation and job enrichment/redesign.

4 Empirical Analysis

4.1 Descriptive evidence: the utilization of generic skills

Table 2 depicts the mean values of the different generic skills calculated by some individual characteristics: gender, educational attainment and occupational group. We used the average scores from the responses to the component items (scale 1 to 5) and normalized them. Therefore, values over 0 indicate that the group develops tasks with an above average intensity of the corresponding skill, and vice versa if the value is below 0.

By gender, it is clear that the overall mean skill content of jobs does not differ that much. However, when the different types of skills are considered a distinct pattern of skill use emerges. That is, men are involved in tasks that ask for a deployment of higher levels of problem-solving, high-level communication, numeracy and technical skills. Alternatively, women's activities are more related to client communication, horizontal communication, literacy and computer skills. Planning skills show a very similar level by gender. These results are quite interesting, for they can be interpreted as providing some confirming evidence on the hypothesis that women would have a comparative advantage in social skills (coordination, interaction, team production) as proposed in Deming (2015),

Table 3 Mean levels of generic competences by firm level characteristics

	New product last 2 years		Use of information sharing-team practices			Technological intensity		
	No	Yes	Low	Medium	High	Low	Medium	High
All skills	–0.221	0.066	–0.201	0.057	0.137	–0.074	–0.012	0.235
Prob. solv	–0.089	0.026	–0.173	0.052	0.118	–0.078	–0.022	0.093
Client com	–0.168	0.056	—0.100	0.019	0.087	–0.081	–0.013	0.085
High com	–0.195	0.060	–0.131	0.054	0.074	–0.062	–0.021	0.076
Planning	–0.155	0.043	–0.145	0.058	0.074	–0.061	–0.002	0.047
Horiz.com	–0.209	0.063	–0.194	0.052	0.137	–0.081	–0.013	0.085
Numeracy	–0.039	0.009	–0.025	–0.031	0.049	–0.026	–0.024	0.041
Basic	–0.044	0.010	–0.001	–0.044	0.037	–0.025	–0.028	0.044
Advanced	–0.027	0.000	–0.047	–0.013	0.054	–0.022	–0.016	0.031
Literacy	–0.231	0.067	–0.186	0.047	0.126	–0.032	–0.023	0.040
Read	–0.174	0.050	–0.172	0.039	0.122	–0.032	–0.001	0.020
Write	–0.240	0.070	–0.158	0.044	0.101	–0.024	–0.042	0.052
Tec. know	–0.190	0.054	–0.181	0.032	0.137	–0.078	–0.010	0.073
Computer	–0.206	0.062	–0.190	0.102	0.083	–0.093	–0.030	0.113

Prob. solv. Problem-solving, *Client com.* Client communication, *High com.* High-level communication, *Horiz. com.* Horizontal communication, *Tec. know.* Technical know-how

Use of information sharing practices: normalized scale created using the presence in the firm of

while man would concentrate (or be located) in tasks that are less prone to interactions (putting attention to specific tasks or giving orders). It is also interesting the large difference in the numeracy skill content of tasks between men and women, considering the important impact of this skill on wages. Note that it is in the more advanced dimension of this skill where the differences are larger. Also, when we split the literacy level of tasks into its components (write and read) women concentrate in tasks where reading seems to be more important.

The table also reveals that, as expected, the higher the level of education attained, the higher the deployment of skills. All the factors present a perfect monotonically increasing trend except problem solving for which the three higher educational levels show a rather similar intensity. In terms of changes over the different levels of education, it can be observed that the main increases in intensity of use are between educational levels 1 and 2, except for client communication, horizontal communication and literacy skills in which the largest change of the means in absolute terms happens between levels 2 and 3. Note that these three skill domains are those in which women show more intensity. Only in the case of high level communication the biggest change is observed between educational levels 3 and 4, which shouldn't be considered a surprise as this skill must be related to management positions for whom a high level of education is usually required.

With respect to the position in the firm, it is apparent that core employees have the lowest levels of utilization for all the skills. We would expect that managers would be using skills more intensively in comparison with supervisors. However, supervisors' jobs involve a higher level of problem solving and horizontal communication skills and are very similar in high-level communication and planning. Indeed, over all, we must notice the very similar level of skill content of jobs between managers and supervisors[7].

In Table 3 we present the mean values of the different generic skills calculated this time by some firm level characteristics, specifically by the introduction of new products, the intensity of use of information sharing arrangements and by our measure of technological intensity. With respect the product strategy of the firm we can observe that innovative firms have a significantly larger intensity of skill use for all the skill domains. All of them show similar differences, except, surprisingly, in the numeracy domain where differences between innovative/non-innovative firms are much smaller (and it doesn't seem to matter if it is advanced or basic).

The relation of the presence of information sharing instruments with the skill content of jobs follows an increasing trend as more instruments are used. Interestingly, the larger change occurs from the low to medium level of intensity, as if the impact on the skill content of the jobs would diminish with the intensity of information sharing. Again, is in the numeracy skill domain where jobs are more similar. The firm technological intensity index appears to be linked

[7] 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 5 are much larger.

Table 4 Determinants of skill content of jobs

	Overall index	Problem-solving	Client communication	High-level communication	Planning skills	Horizontal communication	Numeracy skills	Technical skills	Literacy skills	Computer skills
Supervisor	0.061*	0.207***	0.126***	0.097***	0.016	0.126***	–0.062	0.124***	0.004	–0.052
Core employee	–0.595***	–0.146***	–0.380***	–0.902***	–0.479***	–0.380***	–0.413***	–0.261***	–0.442***	–0.438***
Education level 2	0.176***	0.122***	0.055	0.059*	0.067*	0.055	0.212***	0.285***	0.136***	0.409***
Education level 3	0.324***	0.131***	0.124***	0.181***	0.132***	0.124***	0.356***	0.445***	0.380***	0.529***
Education level 4	0.317***	0.061	0.034	0.293***	0.115**	0.034	0.397***	0.418***	0.432***	0.508***
Experience	0.010**	0.004	0.004	0.012***	0.009*	0.004	–0.001	0.019***	0.009**	0.005
Tenure	–0.008*	–0.005	–0.007	–0.001	–0.005	–0.007	–0.002	–0.010**	–0.006	–0.004
Training	0.277***	0.157***	0.212***	0.197***	0.158***	0.212***	0.177***	0.271***	0.259***	0.184***
# Supervising workers	0.000	0.001	0.000	0.002	0.000	0.000	–0.000	–0.001*	0.000**	–0.001***
Women	–0.022	–0.025	0.039	–0.133***	–0.002	0.039	–0.110***	–0.065**	0.033	0.159***
Product/Process										
Product innovation	0.116***	0.061	0.111***	0.106***	0.051	0.111***	0.011	0.097***	0.114***	0.057
Product strategy	0.021	0.040	0.059**	–0.034	0.044	0.059**	0.011	–0.009	0.007	–0.005
Leadership in market	–0.061**	–0.099***	–0.068**	0.028	–0.057*	–0.068**	–0.090***	–0.015	–0.046	–0.024
Process innovation	–0.047*	0.008	–0.040	–0.075***	–0.021	–0.040	0.054*	–0.071**	–0.040	–0.015
Technological intensity	0.004	0.024	0.008	0.014	–0.000	0.008	0.007	0.031	–0.030	0.058***
Human Resources										
All variable payment	–0.080***	–0.058*	–0.094***	–0.094***	–0.048	–0.094***	0.050*	–0.073***	–0.050*	0.053*
Centralization task	–0.020	–0.021	–0.045**	–0.024	0.013	–0.045**	0.008	–0.006	–0.014	–0.051***
Centralization strategy	–0.018	0.009	–0.026	0.002	–0.010	–0.026	–0.058***	0.015	–0.054***	–0.000
Use of job redesign	0.058**	0.062**	0.036	0.044**	0.011	0.036	0.061**	0.062***	0.046*	0.039
Use of information sharing-teams	0.102***	0.113***	0.112***	0.032	0.094***	0.112***	0.013	0.084***	0.064***	0.029
General firm characteristics										
Export intensity	–0.043**	–0.076***	–0.030	–0.020	–0.066***	–0.030	0.014	–0.038**	–0.046***	–0.028
Belong to a group	0.082**	0.122***	0.083**	0.036	0.039	0.083**	–0.010	0.115***	0.023	0.093**
Size	0.028*	0.020	0.040***	0.035**	0.022	0.040***	0.020	–0.000	0.042***	0.081***
Increasing sales	0.011	0.031*	0.000	–0.019	–0.008	0.000	0.005	0.007	0.027*	0.048***
R2	0.237	0.080	0.146	0.323	0.111	0.146	0.130	0.171	0.200	0.277

$N = 4531$

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

to the utilization of skills, with the sole exception of client communication. However, note that the differences are not that much high, except in the case of computer skills.

4.2 The determinants of the skill content of jobs

Table 4 presents our exploratory analysis of the determinants of the skill content of jobs. We estimate a series of models where the dependent variable is the normalized average score for all the different skill domains as well for the overall score. Estimations use basic OLS with Eiker-White robust standard error that account for the clustering of workers within firms. We have two groups of variables. The first one measures individual level characteristics. We include the traditional variables to proxy for the human capital of the individual, namely education, experience, tenure in the firm and training. Education is measured as a series of dummies for the highest educational level. Experience refers to potential labour market experience and is calculated as age minus 6 and minus the numbers of years of education. Tenure in the firm is measured in years and was reported directly by the employees. Training is a dummy variable that takes value of 1 if workers engaged in a non-legally imposed form of training over the last two years. We also include at the individual level controls for gender, nationality, type of contract and number of hours worked. Firm level controls include our set of key variables discussed in the previous section along with controls for size, firm age, part of a multinational company, belonging to a group, percentage of production exported, whether their market share has been expanding over the last two years and two digit industry classification[8].

With respect the individual level variables, the first aspect to note is the importance of educational level and training in explaining the skill content of the jobs. It is also quite interesting to observe that education is more important than training for the group of job content dimensions related to "cognitive" skills (numeracy, technical, literacy and computer) while the opposite is observed for the rest of skills. This most likely must be related to what is the learning space where these skills are best developed. On the contrary, rather surprisingly, experience and tenure are only modestly related to the skill content of jobs. In fact, in the case of tenure the sign of the coefficients is always negative while is positive for experience. These opposite signs may be related to the transversal nature of the skills considered. We cannot observe clear differences by gender, with the exception of numeracy and technical skills that are more related to jobs developed by men and high-level communication skills that would characterize management type of tasks, where women are less prominent. On the contrary, computer skills are positively related to women.

The results for the firm level variables show different impacts depending on the area they proxy for. With respect product innovation, we can see that innovative firms are characterized by more demanding jobs in terms of skills across all the dimensions considered. This way, the claim that if firms want to develop strategies based on innovative products (high value added products) must have a highly skilled workforce seems to receive support in this data. However, we must also note that the variable that proxies for product market control generally has a negative coefficient. It could be that once the firm has developed a successful product, its focus turns to extract rents from it and some sort of job "deskilling" process activates. Alternatively, it could just reflect that product market prominence is related to a monopolistic type of power and these firms do not have to rely on a more skilled workforce to achieve this position.

A quite different picture emerges from the results related to process technology. In general, the coefficients are negative or insignificant for both the introduction of changes in the production process and the technological complexity of the firm. Our interpretation goes along the lines of a potential introduction of technology to automatize the production process consistent with a deskilling hypothesis. Though maybe only anecdotal, the only coefficient that shows a positive and significant value is the technological intensity variable in the computer skills model.

Finally, our set of variables to account for the relationship between human resource management and skill content of jobs show a rather robust positive relation between modern forms of work organization and skills but a negative impact of variable pay. Taking on the first issue, it is clear that using participative forms of work organization, like teams and job rotation, comes along an increasing skills content of jobs. Considering the large number of controls and the consistent positive value across different dimensions of skills, we can conclude that the complementarity between skills and employee involvement is underscored in this data. It doesn't come that clear the effect of decentralization of decision making on the skill content of jobs. Coefficients on both variables measuring firms' approach to this issue usually show a negative sign, consistent with the idea that when employees have more leverage on decision making they need more skills. However, they statistical significance level is not very powerful, which implies that the correlation is weak or that we are not measuring correctly the underlying concept. Taking on the results of the coefficient measuring the impact of the use of variable payment, they are consistently negative except in the case of numeracy and computer skills. We know that variable payment (pay per performance) elicits more effort from workers but usually there is a trade-off with quality and sometimes it crowds-out others forms of incentives (non-pecuniary). If with the large set of controls we are correctly isolating the incentive effect of variable payment, we may be capturing with this variable the alternative to complex job design (more skill intense) to obtain more effort from employees.

4.3 The returns to skills

The most common strategy to determine the value of generic skills has been the estimation of hedonic wage

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

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 compensated. Therefore, their coefficients are regarded as their shadow prices. Note that a key hypothesis is a labour market that in equilibrium is frictionless in matching worker skills to jobs. In this situation, measures of job characteristics can be used in reverse: as ways to identify the skills possessed by workers. Of course, the higher the barriers to job mobility, the lower the probability of a match between workers and job attributes.

The model we estimate is presented in Eq. (1):

$$\ln W_i = \alpha + Comp_i\beta + HK_i\chi + Ind_i\delta + Firm_i\varnothing + v_i \qquad (1)$$

Where, the dependent variable *lnW* is the logarithm of monthly earnings after taxes. The set of eight generic skills is represented by the matrix *Comp*. The rest of the variables are the same as in the models predicting the use of skills commented in the previous section.

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 proved that it is possible to obtain better estimators by assuming a distribution for the continuous, although unobserved dependent variable, and estimating the model by Maximum Likelihood. The estimator is in fact a generalization of the Tobit model. In order to avoid the well-known sensitivity of the estimation method to the normality in the distribution of the dependent variable, we log-transformed our earnings variable. In addition, we estimated ordered probit models as an alternative to our method that is not dependent on the normality assumption. Results were almost identical. As the results are much more easily interpreted with the technique of interval data (they can be interpreted as in an OLS model), we present these results. Finally, note that all of our estimates report Eiker-White robust standard errors that account for the clustering of workers within firms, which deals with the problem of the correlation of errors generated by the cluster-based sampling frame.

The outcomes of estimating Eq. (1) separately for managers, supervisors and core employees are respectively presented in Table 5, 6 and 7. We estimated several models. In our models 1 to 4, we calculated the return to our set of generic skills without the human capital variables in the model but incorporating the individual and firm level controls. Models 5 to 8 introduce the human capital variables but drop the generic skills variables. Finally, model 9 estimates the full model. We will comment our results separately for each occupational group and provide some summary comments comparing them after it.

4.3.1 Managers

Looking at the full model (model 9 in Table 5), we can observe that client communication skills are the most valued by employers as a one-standard-deviation change confers a 5.6 % increase in monthly earnings[9]. One is tempted to immediately interpret this result as a pay-off for strictly "commercial" abilities. This is certainly part of the pay-off, but we also consider that this variable is capturing some sort of "leadership" activities. High-level communication and numeracy skills are also rewarded, albeit at a more modest level (respectively 3.1 and 3.4 % increase in monthly earnings). Problem solving, planning, horizontal communication and computer skills fail to achieve significance in statistical terms in any of the models estimated. In contrast with these positive returns, there is a large penalization to literacy skills for managers. Negative coefficients are obtained in other papers. Dickerson and Green (2004) found a negative impact of physical skills. They argue that it could be related to a low (even zero) supply price or, more importantly, it could be that manual activities are negatively correlated with other observed and unobserved activities which use positively valued skills. Autor and Handel (2013) develop a formal model where in equilibrium workers are employed in the occupation that has the highest reward to their bundle of tasks. However, this does not imply that each worker receives the maximum market reward to each element in their task bundle. In fact, if the rewards to clusters of tasks are correlated there could be negative cross-occupation correlations between the returns to tasks. In our results, this reasoning implies that in the case of managers there must be some tasks that are negatively correlated with the intensity and the returns to literacy tasks (and hence to literacy skills). Exploring the returns to both numeracy and literacy skills presented in Table 8 (Appendix C), we can see that the return to numeracy skills is concentrated at the higher level of them while for literacy is for writing where we observe the negative coefficient.

In terms of how the inclusion of the different controls change the value and significance of the skill indices coefficients, there are a diversity of results. For those skills that do not seem to influence wages (problem-solving, planning, horizontal communication and computer skills) the results are absolutely independent of the inclusion of different sets

[9] This increase is calculated as $\exp(0.069 \times 0.79) - 1 = 5.6\,\%$, 0.79 being the real standard deviation of the variable.

Table 5 Hedonic wage equations. Returns to Managers

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
Problem-solving	–0.027	–0.020	–0.019	–0.014					–0.008
Client communication	0.084***	0.066***	0.087***	0.069***					0.074***
High-level communication	0.084***	0.062***	0.046*	0.023					0.045*
Planning skills	–0.000	–0.007	–0.007	–0.012					0.005
Horizontal communication	0.008	0.023	–0.021	–0.003					0.021
Numeracy skills	0.060***	0.056***	0.050**	0.048**					0.037**
Technical know-how	0.057*	0.048	0.062**	0.058**					0.033
Literacy skills	–0.015	–0.015	–0.040	–0.048**					–0.059***
Computer use	–0.025	–0.010	–0.035	–0.018					0.019
Education level 2					0.152***	0.148***	0.107**	0.108**	0.105**
Education level 3					0.307***	0.299***	0.254***	0.254***	0.253***
Education level 4					0.454***	0.461***	0.390***	0.394***	0.394***
Experience					0.042***	0.040***	0.041***	0.039***	0.037***
Experience^2					–0.000***	–0.000***	–0.000***	–0.000***	–0.000***
Tenure					0.008	0.012**	0.011**	0.015***	0.016***
Tenure^2					–0.000	–0.000**	–0.000**	–0.000***	–0.000***
Training					–0.077**	–0.079***	–0.108***	–0.113***	–0.120***
MBA					0.191***	0.162***	0.173***	0.139***	0.125***
Individual level controls	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Firm level controls	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Constant	7.683***	7.805***	10.478***	10.461***	6.850***	6.965***	7.605***	7.729	7.594***
St. error of est./Log likelihood	–918.880	–905.191	–879.824	–863.527	–849.185	–830.464	–814.101	–795.262	–782.733
Chi^2/Probability	31.03	60.11	107.88	128.63	186.19	226.41	249.38	298.54	334.48
McKelvey&Zavoina's R^2	0.033	0.057	0.114	0.137	0.184	0.205	0.232	0.252	0.271

$N = 580$
*denotes significant at 10 %; **denotes significant at 5 %; ***denotes significant at 1 %

of controls, even traditional human capital variables. The coefficient on client communication also remains quite similar across the different models and commands a very high payoff regardless of the characteristics of the individual and the firm the manager is working for. Something similar happens with the numeracy skill coefficient, though to a lesser extent as it experiences a reduction of almost a 50 % in its value from the basic model to the full control model. High-level communication is quite sensitive to the inclusion of both individual and firm level control, showing that a large part of the effect disappears once they are introduced in the models. Finally, technical know-how and literacy are more sensitive to the inclusion of controls, especially traditional human capital variables.

With respect the coefficients on the traditional human capital variables, the results are what we could expect. However, it is worth noting three aspects. The returns to the educational level are rather big, especially considering that we are not comparing managers to other occupational groups. A difference of around 40 % on monthly earnings between a manager with a college degree with respect to one with just basic education is certainly considerable. It is also interesting to see that firm level controls have a large impact on the returns to educational levels, while individual controls and the inclusion of the skills indices barely change them. Finally, it is surprising the negative coefficient on training while the specific "training" in the form of an MBA carries on a large payoff.

Table 6 Hedonic wage equations. Returns to Supervisors

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
Problem-solving	–0.001	–0.008	0.005	–0.002					0.002
Client communication	0.006	0.013	0.035***	0.035***					0.028***
High-level communication	0.079***	0.053***	0.039**	0.019					0.016
Planning skills	–0.035*	–0.024	–0.020	–0.011					–0.011
Horizontal communication	–0.004	0.003	–0.007	–0.006					0.003
Numeracy skills	0.064***	0.046***	0.064***	0.052***					0.041***
Technical know-how	0.004	0.008	0.008	0.011					0.005
Literacy skills	0.046***	0.062***	0.017	0.025					0.020
Computer use	–0.025*	–0.008	–0.041***	–0.027*					–0.010
Education level 2					0.107***	0.116***	0.099***	0.111***	0.102***
Education level 3					0.154***	0.195***	0.163***	0.185***	0.159***
Education level 4					0.272***	0.326***	0.287***	0.311***	0.287***
Experience					0.020***	0.020***	0.019***	0.017***	0.016***
Experience^2					–0.000***	–0.000***	–0.000**	–0.000**	–0.000*
Tenure					0.007*	0.005	0.006*	0.005	0.004
Tenure^2					–0.000	–0.000	–0.000	–0.000	–0.000
Training					0.023*	0.029**	0.028**	0.023*	0.012
Individual level controls	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Firm level controls	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Constant	7.304***	7.255***	7.012***	7.237***	6.859***	6.770***	5.372***	5.686***	5.905***
St. error of est./Log likelihood	–1123.878	–1087.336	–1060.771	–1031.606	–1093.304	–1047.287	–1025.051	–993.510	–983.735
Chi^2/Probability	39.38	116.39	205.96	286.36	98.24	255.85	286.82	434.61	477.31
McKelvey&Zavoina's R^2	0.057	0.151	0.206	0.268	0.139	0.245	0.286	0.346	0.362

$N = 630$
*denotes significant at 10 %; **denotes significant at 5 %; ***denotes significant at 1 %

4.3.2 *Supervisors*

Supervisors show some similarities with managers. This way, client communication and numeracy skills also command a positive pay-off, although with a significant reduction in the value with respect to the one observed for managers, especially in the case of client communication skills and only becoming statistically significant when the firm level set of controls are included. Again, problem solving, planning and horizontal communication skills fail to achieve significance in statistical terms in any of the models estimated and computer skills shows an erratic evolution and seems quite dependent on the specific controls included. High-level communication and literacy skills have a positive impact but loses statistical significance in the full model. The fact that the skills rewarded are similar for both managers and supervisors points to consider that their responsibilities must be quite similar. It has to be kept in mind that the firms analyzed are medium and small size firms where the boundaries of some occupations quite often overlap. However, looking at Table 8 (Appendix C) where we split the literacy and numeracy indices in their two components we can observe that for supervisors is the low level of numeracy skills that command a positive payoff, not the advanced ones as in the case of managers. This way, both types of workers may be developing comparable tasks with similar skills needs but with different "intensity" levels that could explain the lower returns that supervisors receive of the skills they deploy in the workplace. The effects of the inclusion of individual and firm level controls on the coefficients are similar to what was observed for managers. For those skills that do not seem to influence wages (problem-solving, planning, horizontal communication and technical skills) the results are absolutely independent of the inclu-

Table 7 Hedonic wage equations. Returns to Core employees

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
Problem-solving	0.016***	0.002	0.008*	0.002					0.000
Client communication	–0.016***	–0.000	–0.000	0.004					0.005
High-level communication	0.057***	0.037***	0.056***	0.040***					0.030***
Planning skills	0.015***	0.018***	0.018***	0.019***					0.016***
Horizontal communication	–0.023***	–0.007	–0.019***	–0.011**					–0.009*
Numeracy skills	0.056***	0.030***	0.040***	0.031***					0.029***
Technical know-how	0.022***	0.011*	0.019***	0.007					–0.002
Literacy skills	0.010	0.019***	0.001	0.006					–0.000
Computer use	–0.001	0.017***	–0.004	0.008					0.003
Education level 2					0.088***	0.075***	0.079***	0.079***	0.074***
Education level 3					0.190***	0.169***	0.182***	0.182***	0.171***
Education level 4					0.279***	0.288***	0.276***	0.276***	0.253***
Experience					0.011***	0.012***	0.013***	0.013***	0.013***
Experience^2					–0.000***	–0.000***	–0.000***	–0.000***	–0.000***
Tenure					0.009***	0.015***	0.009***	0.009***	0.009***
Tenure^2					–0.000***	–0.000***	–0.000***	–0.000***	–0.000***
Training					0.036***	0.033***	0.041***	0.034***	0.028***
Individual level controls	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Firm level controls	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Constant	7.021***	6.828***	7.459***	6.857***	6.702***	6.550***	6.403***	6.041***	5.970***
St. error of est./Log likelihood	–4577.177	–4249.578	–4416.151	–4169.267	–4468.259	–4111.456	–4267.837	–4036.759	–3997.010
Chi^2/Probability	3149	1011.12	603.77	1292.35	447.66	1260.32	1000.69	1576.01	1740.56
McKelvey&Zavoina's R^2	0.064	0.236	0.158	0.274	0.128	0.303	0.235	0.335	0.357

$N = 3149$

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

sion of different sets of controls. Once again, the effect of high-level communication skills disappears when individual and firm level controls are introduced and numeracy is only moderately affected. What's different is that the coefficient on client communication decisively depends on the inclusion of firm level controls and the literacy coefficient shrinks with the inclusion of firm level controls.

With respect the results for the traditional human capital variables, in general, their returns are moderate and stable over the different models estimated. Supervisors are paid for their overall experience but not as much for the number of years they have been around in the firm or their educational level. These results could point to a situation where they are appreciated for what they bring to the firm from outside it, and not in terms of "formal" knowledge (education) but more for their general knowledge of the market or the profession. This hypothesis would explain why training generates a very low pay-off to supervisors, as it would be a measure to "make up" for this general knowledge that "internal" supervisors lack but is necessary to be productive in this position.

4.3.3 *Core employees*

With respect to core employees, we see again that numeracy skills generate a positive pay-off. As it was the case for supervisors but opposite to managers, this payoff comes out of the basic numeracy skills. Core employees also share with managers the positive returns to higher communication skills. For core employees there also is a consistent, albeit not very large, payoff to planning skills. Dickerson and Green (2004) and Garcia Aracil et al. (2004) and Johnes (2005) also reported large and positive impacts on earnings to this type of skill[10]. It is interesting to observe in Table 8 (Appendix C) that the writing component of the literacy skills has a sizable payoff not obtained for supervisors and with the opposite sing for managers. The fact that this positive impact doesn't show up in the general index is related to the negative impact of the reading component of it. Finally, horizontal communication presents a small but negative impact on monthly earnings.

With respect the evolution of the coefficients once the individual and firm level controls are added to the models, we obtain clear indications that they really have an impact, most notably the individual level but also the productive environment where core employees develop their tasks. Only planning skills and to a lesser extent numeracy skills remain stable once controls are included. On the contrary, traditional human capital variables do not impact the coefficients that much.

With respect the models measuring the return to education, experience, tenure and training we obtain clear evidence of a high payoff to all of them. For this occupational group experience and tenure present similar returns and training comes more important than for supervisors and managers. In terms of the coefficients' evolution over the different models the impact of including our large list of controls do not change them dramatically, just mention a more pronounced effect on training.

5 *Summary and discussion*

Summarizing our results, a first general point is that some generic skills carry positive and non-negligible returns across occupations. However, we could observe a pronounced diversity in the payoff to them, increasing with the position of the worker within the firm. A second general point is that 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 individual and firm level characteristics. This result gives support to those studies which advocate the importance of cognitive skills, for instance Johnes (2005), and to some extent differs from the results found by Dickerson and Green (2004)[11].

Client communication skills at the highest positions in the firm, as they are central to firm performance, are highly appreciated by employers. This result would be consistent with the positive impact of product innovation on the skill content of jobs observed in the previous section. The positive impact of high-communication and planning skills for core employees could be interpreted as consistent with the introduction of modern forms of work organization, which we also showed as having a positive impact on the skill content of jobs. These results, along with the positive impact of numeracy skills underscored for the three broad occupations analyzed would provide some support for the hypothesis of a positive correlation between innovative firms and higher skill needs. The non-significant impact of problem-solving skills is in accordance with the findings of Dickerson and Green (2004), whereas Johnes (2005) reported a negative impact on earnings[12].

We turn now our attention to the return of the traditional human capital variables and how these returns were affected once we included in the model our list of skills. As usual, our results show that education, experience and tenure have a large and consistent premium. However, these returns clearly differ across occupations. For managers we observe the largest impact. It is interesting to see, if we compare the coefficients on the educational level for managers and core employees, that their relative size has a constant value (around 40 % bigger) over the different levels of education. Hence, it seems that differences in the return to education are highly dependent on the hierarchical position in the firm more than differences in the impact of education on productivity across occupational levels. Another interesting aspect is that the returns to core employees are actually higher than the returns to supervisors in education and tenure (it is apparent that supervisors are not better paid for a longer tenure) but not for experience. What happens to the human capital variables' coefficients when we introduce in the equation our measures for skills? Basically, the coefficients remain fairly stable. Considering the statistically significant competence coefficients and the coefficients on the traditional human capital variables, we can observe that the highest change has just a 22 % value and the majority of changes are within the 6 %–8 % range. In consequence, there seems to be very little overlapping in the underlying process that generates the returns to both skills and the rest of the human capital variables. In other words, they are capturing something that is different to what education,

[10] 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.

[11] They explain the small negative effect of numerical skills by the presence of a measure of computer skills that are highly correlated and have a substantial positive impact on earnings. We also control for computer skills, but most likely our variable does not offer the same quality of measurement.

[12] In fact, a general comparison with the returns to generic competences in our sample to those reported for the UK shows that ours are clearly lower. We can not claim a perfect match between the samples for these two economies. They mainly differ in that we do not have large companies and that could explain part of the differences in returns. Nevertheless, it could also be related to the lower return to education that characterizes the Catalan labor market.

experience and tenure are proxiyng for. In addition, the overall fit of the model increases when all the variables are added together which means, again, that they explain different things[13].

To explain these results we consider very useful the arguments discussed in the development psychology literature when trying to understand the relationship between education and skills. Bacolod et al. (2010) provide an excellent summary of this research and develop a model to understand the relationship between education and skills. They claim that individual traits and intelligences interact with the environment to produce skills. Traits are stable personal characteristics (personality) determined by the genetic and early environment, while intelligences would be the ability to process contents of the world (traditionally measured with intelligence tests as IQ tests). Again, intelligences are related to genetic endowment and early environment and it is often claimed that early acquisition of intelligences could trigger an accumulation process. Finally, skills are behavioral manifestations of intelligences and traits. Education is an important part of the environment to which individuals are exposed. In this approach education and skills are not equivalent. Instead, education would be an "instrument" or "technology" that helps to transform traits and intelligences into skills. In other words, education (and experience for that matter) would be a mechanism (environmental factor) that would put in motion traits and intelligences to generate skills[14]. Firms could be willing to pay both separately because they will reward workers' skills for the direct impact on productivity and paying for education as a premium for the "insurance" it provides in case an unexpected change generates the need for new or updates skills[15]. To some extent, education would generate some kind of option value while competences would receive a short term payoff directly related to one's productive abilities.

6 Conclusions

In this paper we have presented new empirical evidence within the theoretical framework of the "task approach" to analyze job skill requirements. Departing from the self-evaluation of the content of jobs in terms of 25 tasks, we have derived indices for 8 generic skills: problem-solving skills, client communication, planning skills, high-level communication, horizontal communication, numeracy skills, technical know-how and literacy skills. We first have provided an exploratory analysis on the determinants on the skill intensity of jobs. Consistent with the existing (rather limited) empirical works we have underscored a robust positive correlation between our indices of job skill content and modern forms of workplace organization. Process technological innovation do not show in our data such a clear and positive correlation. Training is an important determinant of job related skills and education seems to have a bigger effect on those skills of a more cognitive nature.

We then have examined the role of generic skills in the determination of earnings for managers, supervisors and core employees. 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 numeracy skills conferred a significant positive pay-off to all workers, regardless 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 and supervisors, and high-level communication skills in addition to planning skills for core employees. We also tested the impact of including in our wage equations both generic skills measures and traditional human capital variables. We do not observe dramatic changes in their coefficients but just a moderate overlapping. Therefore, they appear to be capturing different effects.

[13] Note that inequality has increased within education levels since the 70's (Acemoglu 2002). Wage inequality within education levels, also known as residual inequality, could 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.

[14] This idea is very much in line with Bishop's claim that cognitive skills act as tools which enable the acquisition of occupation specific skills (Bishop 1995).

[15] In the literature on technological change, there is a long tradition of considering education as a mediator factor. Nelson and Phelps (1966) claim that education facilitates the introduction of new ideas because highly educated people can better discriminate what is a valuable idea or not. Bartel and Lichtenberg (1987) provide evidence showing that more educated people have a higher capacity to assimilate new ideas. More recently, Greenwood and Yorukoglu (1997) argued that education is in fact the key element that allows firms to adopt new technologies.

Appendix A

Skill indices construction

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. To our initial set of 26 tasks we excluded the use of computer equipment because we preferred to assess its impact on earnings separately. Hence, we applied factor analysis on the remaining 25 tasks.

We proceeded calculating the factors and applying an orthogonal rotation in order to aid interpretation. Table A.2 presents the factor loadings that depict the strength of the relationships between each of the initial tasks 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 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 factor 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 A.2 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. 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. Second, the internal consistency of the factors measured by the Cronbach's Alphas was rather high. 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. Finally, each variable appears related at most to one factor (figures in bold in Table A.2). 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 degree of subjectivity, it is primarily the consequence of common sense applied to the data. 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.

Table A.1 Initial set of tasks

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
Counseling, 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	

Table A.2 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 own-self	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 con-tinuosly	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 calcula-tions	0.2463	0.0945	0.1198	0.1154	0.0318	**0.6931**	0.0951	0.0392	0.4107
Complex cal-culations	0.2449	0.1686	0.1427	0.0991	0.0449	**0.7122**	0.1036	0.088	0.3538
Spotting prob-lems	**0.7775**	0.0435	0.1128	0.1342	0.1198	0.1816	0.0547	0.021	0.3122
Cause of prob-lems	**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 mis-takes	**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 commu-nication**	**High–level commu-nication**	**Planning skills**	**Horizontal commu-nication**	**Numeracy skills**	**Technical knowl-edge**	**Literacy skills**	
Standard devi-ation	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	

Factor analysis applied on 4,760 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

Appendix B

Table B.1 Descriptive Statistics

Dependent variable: earnings					
Managers		**Supervisors**		**Core employees**	
Interval	**%**	**Interval**	**%**	**Interval**	**%**
0–2,000 €	31.99 %	0–1,000 €	4.12 %	0–700 €	4.39 %
2,001–2,600 €	27.77 %	1,001–1,300 €	25.04 %	701–1,000 €	33.28 %
2,601–3,200 €	19.86 %	1,301–1,600 €	25.54 %	1,001–1,300 €	36.96 %
3,201–3,800 €	10.19 %	1,601–1,900 €	20.26 %	1,301–1,600 €	15.54 %
3,801–4,400 €	5.10 %	1,901–2,200 €	12.03 %	1,601–1,900 €	6.69 %
4,601–5,200 €	2.46 %	2,201–2,500 €	8.07 %	1,901–2,200 €	1.94 %
5,201–5,800 €	1.05 %	2,501–2,800 €	3.13 %	2,201–2,500 €	0.71 %
> 5,800 €	1.58 %	> 2,800 €	1.81 %	> 2,500 €	0.48 %

Means reflect percentages in dummy variables. No standard deviations for dummy variables are shown

Table B.2 Descriptive Statistics

Independent variables

	Total Sample			**Managers**			**Supervisors**			**Core employees**		
	N	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**
Factor analysis Problem-solving	4,347	0.00	0.92	568	0.00	0.73	630	0.19	0.65	3,149	–0.04	1.00
Client communication	4,347	0.00	0.86	568	0.29	0.79	630	0.00	0.82	3,149	–0.06	0.87
High-level communication	4,347	0.00	0.84	568	0.64	0.63	630	0.71	0.59	3,149	–0.26	0.77
Planning skills	4,347	0.00	0.83	568	0.16	0.57	630	0.18	0.56	3,149	–0.07	0.90
Horizontal communication	4,347	0.00	0.79	568	0.00	0.58	630	0.07	0.61	3,149	–0.01	0.85
Numeracy skills	4,347	0.00	0.81	568	0.32	0.72	630	0.10	0.79	3,149	–0.08	0.81
Technical know-how	4,347	0.00	0.70	568	0.15	0.54	630	0.10	0.58	3,149	–0.05	0.74
Literacy skills	4,347	0.00	0.62	568	0.19	0.64	630	0.33	0.61	3,149	–0.04	0.60
Computer use	4,347	0.00	1	568	0.59	0.57	630	0.30	0.81	3,149	–0.17	1.04
Average score Problem-solving	4,347	4.03	0.80	568	4.18	0.60	630	4.30	0.55	3,149	3.95	0.86
Client communication	4,347	2.63	1.16	568	3.21	0.97	630	2.86	1.05	3,149	2.48	1.18
High-level communication	4,347	2.81	1.12	568	3.77	0.75	630	3.72	0.75	3,149	2.45	1.03
Planning skills	4,347	3.96	0.89	568	4.35	0.55	630	4.30	0.61	3,149	3.81	0.95
Horizontal communication	4,347	3.88	0.79	568	4.13	0.54	630	4.20	0.55	3,149	3.76	0.84
Numeracy skills	4,347	2.65	1.17	568	3.23	0.98	630	2.97	1.08	3,149	2.48	1.17
Technical know-how	4,347	3.39	1.06	568	3.87	0.70	630	3.75	0.82	3,149	3.23	1.12
Literacy skills	4,347	2.48	1.02	568	3.08	0.83	630	2.85	0.89	3,149	2.29	1.01
Computer use	4,347	3.39	0.71	568	3.84	0.44	630	3.77	0.50	3,149	3.23	0.72
Female	4,347	0.31	0.46	568	0.22	0.41	630	0.27	0.43	3,149	0.34	0.47
Spanish[a]	4,347	0.95	0.21	568	0.98	0.15	630	0.99	0.11	3,149	0.95	0.23
Education Level 1[a]	4,347	0.47		568	0.10		630	0.37		3,149	0.57	
Education Level 2	4,347	0.25		568	0.24		630	0.29		3,149	0.24	
Education Level 3	4,347	0.19		568	0.31		630	0.23		3,149	0.15	
Education Level 4	4,347	0.09		568	0.33		630	0.11		3,149	0.04	
Experience	4,347	20.01	10.85	568	21.87	9.77	630	22.13	10.52	3,149	19.22	11.13
Experience^2	4,347	518.15	500.40	568	574.85	476.9	630	600.6	530.57	3,149	490.73	498.2
Tenure	4,347	9.24	8.43	568	11.41	8.84	630	11.63	8.72	3,149	8.34	8.59
Tenure^2	4,347	156.46	273.28	568	202.07	280.97	630	211.37	303.91	3,149	136.50	262.48
MBA				568	0.09	0.28	630			3,149		
Training	4,347	0.38	0.48	568	0.77	0.42	630	0.62	0.86	3,149	0.41	0.72
Temporary contract	4,347	0.12	0.32	568	0.04	0.19	630	0.44	0.199	3,149	0.15	0.35
Hours worked < 35	4,347	0.09		568	0.07		630	0.07		3,149	0.09	
Hours worked < 40[a]	4,347	0.77		568	0.59		630	0.70		3,149	0.81	
Hours worked > 40	4,347	0.15		568	0.34		630	0.22		3,149	0.09	

Table B.2 Descriptive Statistics (Continued)

Independent variables	Total Sample			Managers			Supervisors			Core employees		
	N	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**	**N**	**Mean**	**St. D.**
Food industry[a]	4,347	0.12		568	0.12		630	0.12		3,149	0.12	
Electronic and other elec. equipment	4,347	0.93		568	0.14		630	0.08		3,149	0.09	
Hotel industry	4,347	0.80		568	0.05		630	0.10		3,149	0.08	
Computer & related activities	4,347	0.91		568	0.13		630	0.06		3,149	0.09	
Human health services	4,347	0.12		568	0.11		630	0.13		3,149	0.11	
Rubber and plastic materials	4,347	0.78		568	0.08		630	0.11		3,149	0.07	
Fabricated metal products, exc. machinery	4,347	0.20		568	0.16		630	0.19		3,149	0.21	
Machinery and equipment	4,347	0.16		568	0.15		630	0.16		3,149	0.17	
Furniture	4,347	0.51		568	0.04		630	0.06		3,149	0.05	
Log number of workers	4,347	3.53	1.00	568	3.63	0.95	630	3.63	1.01	3,149	3.50	1.00
Firm belongs to a group	4,347	0.15	0.35	568	0.16	0.37	630	0.19	0.39	3,149	0.13	0.34
% Exports over sales	4,347	1.84	0.804	568	1.73	0.75	630	1.79	0.80	3,149	1.87	0.81
Firm age	4,347	1,976.78	23.3	568	1,977.55	21.8	630	1,977.44	21.08	3,149	1,976.48	24.05
Product strategy	4,347	0.51	0.49	568	0.56	0.49	630	0.53	0.49	3,149	0.49	0.49
Leadership in product market	4,347	0.32	0.43	568	0.37	0.46	630	0.33	0.44	3,149	0.31	0.43
Multinational	4,347	0.071	0.26	568	0.08	0.27	630	0.07	0.26	3,149	0.68	0.25
Process innovation	4,347	0.55	0.49	568	0.58	0.48	630	0.57	0.49	3,149	0.55	0.49
Variable payment	4,347	0.67	0.45	568	0.72	0.44	630	0.71	0.44	3,149	0.66	0.46
Centralization key decisions	4,347	–0.035	0.85	568	–0.04	0.84	630	–0.03	0.89	3,149	0.04	0.85
Centralization task decisions	4,347	–0.041	0.74	568	–0.15	0.73	630	–0.04	0.70	3,149	0.02	0.75
Technological intensity	4,347	2.08	0.76	568	2.16	0.75	630	2.09	0.77	3,149	2.07	0.76
Information sharing-teams	4,347	0.05	0.69	568	0.05	0.71	630	0.08	0.71	3,149	0.05	0.69
Job redesign	4,347	0.084	0.63	568	0.10	0.62	630	0.10	0.64	3,149	0.89	0.63

Means reflect percentages in dummy variables. No standard deviations for dummy variables are shown
[a]Referential variables in the regressions

Appendix C

Table 8 Hedonic wage equations. Decomposition of returns to numeracy and literacy skills

	Managers	Supervisors	Core employees
Problem-solving	–0.014	–0.007	–0.004
Client communication	0.076***	0.024**	0.003
High-level communication	0.049**	0.010	0.027***
Planning skills	0.006	–0.015	0.014***
Horizontal communication	0.019	–0.000	–0.009*
Numeracy skills	0.036	0.001	–0.002
Read	0.002	0.008	–0.009
Write	–0.046***	0.001	0.013**
Mat1	–0.013	0.023*	0.032***
Mat2	0.054***	0.014	–0.006
Computer use	0.023	–0.009	0.001
Education level 2	0.117**	0.100***	0.070***
Education level 3	0.258***	0.159***	0.164***
Education level 4	0.400***	0.290***	0.245***
Experience	0.035***	0.016***	0.012***
Experience^2	–0.000***	–0.000*	–0.000***
Tenure	0.018***	0.004	0.008***
Tenure^2	–0.000***	–0.000	–0.000***
Training	–0.128***	0.014	0.028***
Individual level controls	Yes	Yes	Yes
Firm level controls	Yes	Yes	Yes
Constant	7.779***	5.854***	6.012***
St. error of est./Log likelihood	–780.810	–984.075	–3987.904
Chi^2/Probability	340.45	477.18	1784.00
McKelvey&Zavoina's R^2	0.275	0.369	0.355

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

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Ferran Mane is an associate professor at the Rovira i Virgili University. BS in Economics, Autonomous University of Barcelona; MPS, Cornell University; PhD in Economics, Autonomous University of Barcelona. He has been Visiting Fellow at Essex University, Cornell University and University of California-Davis. He has worked as a consultant for Cedefop and ILO. He has published several articles and chapters in books on vocational education, the effects of on-the-job training on workers productivity, changes in the American education system and the effects of technological change on education and occupational structures.

Daniel Miravet is a PhD graduate in Economics at Universitat Rovira i Virgili. He works as a mobility manager at ATM del Camp de Tarragona, public agency of the Catalan regional Goverment which coordinates the public transport system at the metropolitan level. He is also a part-time lecturer at the Economics Department of Universitat Rovira i Virgili. His research interests involve economics of education, competencies, labour market and transport economics.