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1. Dual Labour Markets and (Lack of) On-The-Job Training: Evidence for Spain using PIAAC data

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1. Dual Labour Markets and (Lack of) On-The-Job Training: Evidence for Spain using PIAAC data

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Abstract

Using the Spanish micro data in PIAAC, we first document how the excessive dualism of the Spanish labour market leads to lower on-the-job training for temporary workers than for permanent workers. Next, we find that that the lower specific training received by temporary workers has a detrimental effect on their literacy and numeracy scores in the PIAAC study.

Keywords

Dual labour market, Total factor productivity, On-the-job training, Cognitive skills.

Introduction

Among the most salient features of the Spanish economy during the last twenty years or so we find the following two : (i) a strong labour-market segmentation stemming from large differences in employment protection legislation (EPL henceforth) that encourage the widespread use of temporary / fixed-term contracts, and (ii) a sharp reduction in the growth rate of Total Factor Productivity (TFP henceforth), a multifactor productivity variable that captures investment in R&D and the level of human capital of accumulated by employers and workers.

The origin of the first feature dates back to the mid-eighties when, in order to ameliorate the sharp rise in unemployment after the two oil price crises and the re-industrialization process during the transition to democracy, a radical labour market reform was passed in 1984. This reform allowed the indiscriminate use of temporary contracts (with either reduced or no costs for dismissal) for any regular productive activity (and not just for seasonal employment, as it had been the case until then), while keeping the rigid employment protection of permanent contracts unchanged through high severance pay (see, e.g., Dolado et al., 2002 and 2008).

The rate of temporary work (i.e., the share of workers under temporary contracts in the total number of employees) soared from 15% before the reform to 35.4% in the mid-nineties. Since then, around 90% (94% nowadays) of newly signed contracts have been of this type, while the average temp-to-perm conversion rate has oscillated between 10% in the nineties and first half of the 2000s and 5% nowadays (see Amuedo-Dorante, 2001 and Güell and Petrongolo, 2007). Later on, after a long sequence of partial labour market reforms, the rate of temporary work stabilized at around 30%. Even after the mass destruction of temporary jobs in Spain during the Great Recession, it has dropped to only to 24%, which still remains one of the highest rates in the OECD.

As regards the second feature, labour productivity growth has seen a significant slowdown over the long boom (1995-2007) that preceded the Great Recession, when both employment and hours worked experienced a sharp growth. It is important to highlight that this reduction of labour productivity growth was not due to a slowdown in the accumulation of physical capital per worker, as a result of the strong job creation. Rather, it was due to a sharp decline in the growth rate of TFP, which went down from an average of 1.5% in 1980-1994 to -0.35% in 1995-2007. Although a substantial part of this decline has been due to the heavy dependence of the Spanish economy on several low value-added sectors (e.g., construction, tourism, catering, etc..), there is extensive evidence documenting that TFP growth has also performed rather poorly in several tradable sectors, such as the manufacturing industry (see, e.g., Escribá and Murgui, 2009).

This negative performance of the TFP growth rate in Spain is rather puzzling since it took place during a period of large technological improvements worldwide. In particular, it contrasts not only with the US, where TFP growth sharply accelerated, but also with the rest of Europe where, despite a certain slowdown, TFP has evolved considerably better than in Spain. So, according to EU KLEMS (a harmonized database of multifactor productivity in EU countries) the average TFP growth rate in the EU-15 fell from 2.7% in 1970-1994 to 1.3% in 1995-2005 while, as discussed above, the corresponding reduction of TFT growth in Spain has been much larger (see Escribá and Murgui, 2009).

Our goal in this paper is to establish a link between the two above-mentioned features using a mechanism that so far has not received too much attention in the literature. Specifically, we analyze how the gap in EPL strictness between permanent and temporary contracts may have reduced the amount of on-the- job training (OJT henceforth) that temporary employees receive the workplace. In addition, we explore whether this detrimental effect on OJT also translates into changes in temporary workers' cognitive skills and competences, and thus ultimately affect their accumulation of human capital. The cross –sectional database for Spain available in the first wave of the Programme for the International Assessment of Adult Competencies (PIAAC) allows us to jointly explore these two effects. The basic insight of our approach is that, in a context of wage rigidity and a high EPL gap between temporary and permanent workers, firms seem far less inclined to turn unstable contracts into stable ones. This causes temporary contracts to change from being "probationary contracts" (*stepping stones*) to become "terminal contracts" (*dead-ends*) leading to a very high worker turnover between employment and unemployment. Insofar as the EPL gap cannot be neutralized through enough wage flexibility, firms have little incentive to invest in the training their employees. By the same token, neither workers have the right incentives to improve on their job performance by accumulating better productive capabilities. Since these skills and OJT are very important components of multifactor productivity, this mechanism may have played an important role in explaining the relation between labour market duality and the unsatisfactory development of TFP growth (see Bassaninni et al., 2008).

This type of mechanism has been recently proposed by Dolado et al. (2013) using a model where the decisions of employers and workers interact in a dual labour market inspired by the characteristics of the Spanish one. The setup that these authors consider is one in which firms find it optimal to initially hire workers under fixed-term contracts. When such contracts expire (typically after 1 or 2 years), the employers face the decision to upgrade the worker to a permanent contract (subject to dismissal costs / much higher EPL) or to dismiss the worker and hire another one again in sequence on a temporary basis.

Temporary workers set the optimum level of effort/productivity in their jobs by trading off the disutility of exerting effort and the utility provided by a combination of the wage received in a temporary job and the expectation of promotion to a permanent job at the end of the fixed-term contract. Firms with temporary jobs take decisions on wages, contract conversion rates and investment on occupational training, so as to maximize expected benefits subject to workers' participation and incentive compatibility constraints.

Dolado et al.'s (2013) show that, insofar as wage rigidity prevents the neutralization of the severance pay effects in collective bargaining, as is the case in Spain, an increase in the EPL gap between the two types of workers (i.e., larger labour-market dualism) not only leads to less investment by firms on OJT, but also implies a reduction in workers' effort. The basic insight for this result is that a higher EPL gap reduces the temp-to-perm conversion rate. Therefore, firms do not find it profitable to invest in the training of temporary workers who are very unlikely to b eupgraded. This gives rise to a disappointment effect among workers, who respond to the lower and more uncertain promotion prospects by exerting less effort. Hence, this leads to a self-fulfilling prophecies equilibrium where employers do not invest in workers, expecting that they will not exert enough effort, and workers fulfill these expectations by rationally anticipating firms' strategies.

For the empirical test of their model, these authors use the *Survey of Business Strategies* (SBS), conducted by the SEPI Foundation. The SBS provides firm-level longitudinal information on a representative sample of manufacturing firms in Spain during 1991-2005 which, for each year and firm in the survey, allows to compute both the growth rate of TFP and the conversion rate of temporary workers into permanent ones.

By means of panel regression methods (controlling for a wide range of socio-economic and demographic variables for both workers and firms), their main empirical finding is that an increase of the EPL gap leads to reductions in the conversion rate in those firms with a higher rate of temporary work which, in turn decreases their TFP growth rate. The opposite is found when the EPL gap goes down (as happened, for example, after the changes in labour market regulation in the reforms of 1994 and 1997). Furthermore, they document that, since the early 2000s, the slowdown in TFP is particularly concentrated in those manufacturing industries intensive in temporary work rates that are ancillary linked to the construction sector (cement, wood and furniture, etc.),where a bubble started to grow in the early 2000s.

One problem of the SBS is that it lacks information on both firm-provided training activities at the workplace and the effort exerted by employees. The availability in PIAAC of different measures of OJT activities for workers as well as on their scores in the literacy and numeracy tests allows us to overlook, at least in part, this deficiency. Hence, using the cross-sectional sample for Spain in PIAAC, our main goal here is to check, firstly, whether there is a direct causal relation between the type of contract held by the worker and the amount of OJT received at the workplace and, secondly, whether enjoying this type of training increases literacy and numeracy skills.

In order to derive testable hypotheses in our empirical approach, we start by developing a simple model of a two-tier labour market where job vacancies opened by firms differ according to the educational attainment of job seekers. For simplicity it is assumed that firms offer permanent contracts (with high dismissal costs) to highly-educated workers, while temporary contracts (without dismissal costs) are only available for less-educated workers. Before entering the labour market, individuals (who differ in their innate ability and therefore in the cost of education) select their preferred level of education according to the expected utility to be achieved in each type of job. The main result of the model is that, in the presence of rigid wages and aggregate productivity shocks that drive job destruction, greater labour market dualism reduces workers' incentives to improve their level of education, especially during booms. Other important predictions are that, on the one hand, growing specialization in sectors in which temporary work is more intensive reduces workers' human capital accumulation and, on the other hand, that investment in education exhibits, *ceteris paribus*, a counter-cyclical pattern since its opportunity cost is lower in recessions.

In general, our empirical results support these theoretical implications. First, using a large number of controls on individual and job characteristics (including worker's motivation), we find a substantially negative and statistically significant relationship between holding a temporary contract and the amount of OJT received at the workplace. Secondly, we find that the less OJT individuals receive, the worse their literacy and numeracy skills. These results turn out to be consistent with the growing empirical evidence about the negative effects of persistent labour market dualism in Spain on productivity growth and unemployment (see Bentolila et al., 2012).

The rest of the paper is structured as follows. Section 2 provides a brief overview of the related literature in Spain on this topic. Section 3 develops a simple theoretical model that guides our empirical approach. Section 4 describes the PIAAC database and provides descriptive statistics of the outcome and treatment variables used in the empirical analysis. Section 5 presents the main empirical results. Finally, Section 6 offers some brief conclusions.

RELATED LITERATURE

In addition to the previously discussed paper by Dolado et al. (2013), there are some other related works, focusing on the Spanish case, that examine the effects of segmentation in the labour market on productivity growth. We next summarize their main conclusions.

Possibly the first paper addressing this issue is Sánchez and Toharia (2000) who, on the basis of the main implications of a standard efficiency wage model, use data from the SBS for the period 1991-1994 to estimate the relationship between the rate of temporary work and labour productivity growth. Specifically, they regress average labour productivity on the rate of temporary work at the firm level, plus other controls, finding a negative relationship between both variables. Similar results been obtained by Alonso-Borrego (2010) and Gonzalez and Miles (2012) using more updated samples drawn from the Firms' Balance Sheets of the Bank of Spain (CBBE) and the SBS, respectively. Like Dolado et al. (2013), these authors focus on documenting the negative effect of contractual instability on the growth rate of TFP, rather than on labour productivity growth. Yet, they ignore the mechanism linking conversion rates and TFP which is stressed by the latter authors.

Regarding the relationship between dualism and the incidence of occupational training in Spain, it is worth highlighting the work of Alba-Ramirez (1994) and De la Rica et al. (2008). In both cases, they document that firms invest less in training temporary workers given their high turnover rates, although they do not examine how the amount of training has varied with the changes observed in the EPL gap which have taken place since the initial labour market reform in 1984.

Recently, Garda (2013) analyzes the size of wage losses experienced by those workers who have been displaced to other firms as a result of having been subject to a collective dismissal (ERE) in their previous firm. If firms provide a higher level of specific training to workers with permanent contracts than to those with temporary contracts, the loss of this type of human capital will be more significant for the first type of workers than for the second. Therefore, we would expect to find higher wage losses among workers with permanent contracts. Using the Social Security records from the Continuous Sample of Working Lives (MCVL) and controlling by job tenure, sector of activity and other covariates, the results confirm that permanent workers subject to EREs suffer higher and more permanent wage cuts than those with temporary contracts.

A MODEL OF EDUCATIONAL CHOICE IN A DUAL LABOUR MARKET

Preliminaries

In our model, workers and firms live for two periods and, for simplicity, we assume that there is no time discounting. At the beginning of the first period, workers apply for jobs after having chosen their educational level. Firms have a linear technology and only hire workers whose expected value for the company, *W*, is equal to or greater than their hiring costs. The initial skill of the worker is denoted by $\theta \in \left[\underline{\theta}, \overline{\theta}\right]$ and we assume that its distribution is uniform. Human capital is a composite of skill and education. Again, for the sake of simplicity, we assume that there are only two levels of education, and that the human capital of a highly-educated worker is $H^e(\theta) = h\theta$, where *h> 1*, while the human capital of a less-educated worker is $H^u(\theta) = \theta$. The cost of acquiring education $C(\theta)$ is assumed to be decreasing in θ. Specifically, we choose the functional form $C(\theta) = \theta^{-\gamma}$, where $\gamma > 0$.

Once the education decision has been made, firms hire workers either using temporary (T) or permanent contracts (P). The difference between these two types of contracts is that dismissing a worker with a P contract involves a firing cost $F > 0$, while there is no dismissal compensation for temporary workers. To simplify the analysis, we assume that P contracts are only offered to workers with high education, while those jobs available for the T workers do not have this requirement. Therefore, workers without education start in T job positions whose initial productivity is equal to their human capital, while educated workers start in P job positions whose initial productivity is equivalent to $\zeta = h\theta$.

In the second period, workers' productivity changes due to an aggregate shock that captures business cycle fluctuations. In particular, during this period, the productivity of the less-educated workers is perceived by firms with T jobs to be uniformly distributed $U\left[\overline{\theta}(1-\varepsilon), \overline{\theta}\right]$, where $\varepsilon \in [0,1]$ is a parameter of the distribution, for which it holds that $\underline{\theta} = \overline{\theta}(1-\varepsilon)$. As a result of this assumption, the p.d.f and c.d.f of the productivity for this kind of worker during the second period are: $g_\theta(\varepsilon) = \frac{1}{\varepsilon\overline{\theta}}$ and $G_\theta(\varepsilon) = 1 + \frac{\theta - \overline{\theta}}{\varepsilon\overline{\theta}}$, respectively. Likewise, the corresponding distribution of productivity perceived by firms with P jobs for workers with higher educational level is $U\left[\overline{\zeta}(1-\varepsilon), \overline{\zeta}\right]$, where $\overline{\zeta} = h\overline{\theta}$, so that $g_\zeta(\varepsilon) = \frac{1}{\varepsilon\overline{\zeta}}$ and $G_\zeta(\varepsilon) = 1 + \frac{\zeta - \overline{\zeta}}{\varepsilon\overline{\zeta}}$. Notice that in both cases a higher (lower) value of ε captures a recessionary (expansionary) phase in which the average productivity of workers in both types of firms drops (increases).

Wages in P and T jobs are denoted as w_P and w_T, respectively, and are taken to be not fully flexible. In order to simplify the analysis, it is assumed that these wages are only paid in the second period and are posted by firms at the beginning of the first period. They verify that $w_T < w_P$, and are set by firm subject to the constraints $F < w_P < F + 0.5\bar{\zeta}\left(= F + 0.5h\bar{\theta}\right)$ and $0 < w_T < 0.5\bar{\theta}$. As will be argued below, these restricted ranges of wage variation, while capturing some degree of wage rigidity, ensure that workers always prefer working to not working. Therefore, the participation constraints are satisfied.

Finally, another relevant assumption is the existence for workers in T jobs of a rate of voluntary quits, q, with $0 < q < 1$, during the second period (reflecting the unexpected termination of temporary employment which is not due to a negative shock). By contrast contrary, workers in P jobs never quit.

Asset values

(I) Firms

Firms hire workers whenever the expected value of their contribution to the firm's profits is greater than the hiring cost, HC, which is taken to be identical for both types of jobs.

Denoting the asset value of a firm which offers contracts of a given type as $W_i \ (i = P,\ T)$, the following asset value is obtained for firms with P jobs,

$$W_P(\varepsilon,\zeta) = \zeta - HC + \left[\int_{\bar{\zeta}(1-\varepsilon)}^{\bar{\zeta}} \max(\zeta - w_P, -F)\, dG_\zeta(\varepsilon)\right] =$$

(using integration by parts, see Appendix)

$$= \zeta - HC + \left[\left(\bar{\zeta} - w_P\right) - \int_{w_P - F}^{\bar{\zeta}} G_\zeta(\varepsilon)\, d\zeta\right] \qquad (1)$$

Regarding firms offering temporary jobs, their asset value is,

$$W_T(\varepsilon,\theta) = \theta - HC + (1-q)\left[\int_{\bar{\theta}(1-\varepsilon)}^{\bar{\theta}} \max(\theta - w_T, -F)\, dG_\theta(\varepsilon)\right] =$$

$$= \theta - HC + (1-q)\left[\left(\bar{\theta} - w_T\right) - \int_{w_T}^{\bar{\theta}} G_\theta(\varepsilon)\, d\theta\right]. \qquad (2)$$

Note that the terms $w_P - F$ and w_T in expressions (1) and (2) turn out to be the productivity cutoffs used by firms to keep their workers in P and T jobs, respectively. In other words, this means that workers with productivities $\zeta < w_P - F$ and $\zeta < w_P - F$ will see their contracts terminated in the second period. From the value of these cutoffs it can be inferred that a wage rise increases the job destruction rate while a rise in severance payments, F, reduces that rate for workers with P jobs. This is because, upon having to pay higher dismissal costs, firms will prefer keep some workers whose productivity has fallen and who would have been dismissed under lower severance pay. Specifically, using the uniform distributions $\zeta \sim U\left[h\bar{\theta}(1-\varepsilon), h\bar{\theta}\right]$ and $\theta \sim U\left[\bar{\theta}(1-\varepsilon), \bar{\theta}\right]$ with $\varepsilon \in [(0,1]$ we can write,

$$W_P(\varepsilon,\theta) = h\theta - HC + \left[\frac{\left(h\bar{\theta} - w_P + F\right)^2}{2\varepsilon h\bar{\theta}} - F\right] \tag{3}$$

$$W_T(\varepsilon,\theta) = \theta - HC + (1-q)\left[\frac{\left(\bar{\theta} - w_T\right)^2}{2\varepsilon\bar{\theta}}\right]. \tag{4}$$

(II) Workers

As for workers, assuming for the sake of simplicity that the value of being unemployed is equal to zero, their asset values, V_i, of being employed with a P and T contract are as follows,

$$\begin{aligned} V_P(\varepsilon,\theta) &= \left[\int_{w_P - F}^{h\bar{\theta}} w_P dG_\zeta(\varepsilon) + \int_{h\bar{\theta}(1-\varepsilon)}^{w_P - F} F dG_\zeta(\varepsilon)\right] - C(\theta) = \\ &= \frac{w_P h\bar{\theta}}{\varepsilon h\bar{\theta}} - \frac{(w_P - F)^2}{\varepsilon h\bar{\theta}} - \frac{Fh\bar{\theta}(1-\varepsilon)}{\varepsilon h\bar{\theta}} - C(\theta) \\ &= \frac{(w_p - F)\left[h\bar{\theta} - (w_P - F)\right]}{\varepsilon h\bar{\theta}} + F - C(\theta) \end{aligned} \tag{5}$$

$$\begin{aligned} V_T(\varepsilon,\theta) &= (1-q)\left[\int_{w_T}^{\bar{\theta}} w_T dG_\zeta(\varepsilon)\right] = \\ &= (1-q)\left[\frac{w_T\bar{\theta}}{\varepsilon\bar{\theta}} - \frac{w_T{}^2}{\varepsilon\bar{\theta}}\right] = (1-q)\left[\frac{w_T\left(\bar{\theta} - w_T\right)}{\varepsilon\bar{\theta}}\right] \end{aligned} \tag{6}$$

Given these derivations, note that V_P and V_T are strictly positive in (5) and (6) since the admissible productivity thresholds for workers in jobs P and T are, respectively, $w_P - F$ and w_T. As a result, it follows that $w_P - F < h\bar{\theta}$ and $w_T < \bar{\theta}$ so that the participation constraint is satisfied, meaning that workers prefer to work than not to work.

Decisions on education

According to the previous asset values, at the beginning of the initial period the worker will decide to invest in education if the net gains of getting educated outweigh the net gains of not doing so. That is, workers decide to invest in education if,

$$\frac{(w_p - F)\left[h\bar{\theta} - (w_P - F)\right]}{\varepsilon h\bar{\theta}} + F - \theta^{-\gamma} \geq (1-q)\left[\frac{w_T(\bar{\theta} - w_T)}{\varepsilon\bar{\theta}}\right] \tag{7}$$

from which it follows that an initial skill threshold θ^* can be defined such that those individuals with $\theta < \theta^*$ would not invest in education while that those with $\theta \geq \theta^*$ will do. From (7), it follows that θ^* can be re-written as,

$$\theta^* = \frac{1}{D^\gamma}, \qquad \text{where}$$

$$D = \frac{(w_p - F)\left[h\bar{\theta} - (w_P - F)\right]}{\varepsilon h\bar{\theta}} + F - (1-q)\left[\frac{w_T(\bar{\theta} - w_T)}{\varepsilon\bar{\theta}}\right]. \tag{8}$$

Comparative Statics

Since for any predetermined variable, x, $\partial\theta^*/\partial x = (\partial\theta^*/\partial D)(\partial D/\partial x)$ and $\partial\theta^*/\partial D < 0$ the following comparative statics results can be derived,

$$\frac{\partial\theta^*}{\partial w_P} < 0, \text{ given that } sign\frac{\partial D}{\partial w_P} = sign\left[h\bar{\theta} - 2(w_P - F)\right] > 0 \tag{9}$$

$$\frac{\partial\theta^*}{\partial w_T} > 0, \text{ given that } sign\frac{\partial D}{\partial w_T} = sign\left\{-(1-q)\left[\bar{\theta} - 2w_T\right]\right\} < 0 \tag{10}$$

$$\frac{\partial\theta^*}{\partial F} > 0, \text{ if and only if } \varepsilon < 1 - \frac{2(w_P - F)}{h\bar{\theta}}, \text{ then } sign\frac{\partial D}{\partial F} = sign\left\{\frac{2(w_P - F)}{\varepsilon h\bar{\theta}} - \frac{1-\varepsilon}{\varepsilon}\right\} \tag{11}$$

$$\frac{\partial\theta^*}{\partial q} < 0, \text{ given that } sign\frac{\partial D}{\partial q} > 0 \tag{12}$$

$$\frac{\partial\theta^*}{\partial\varepsilon} > 0, \text{ given that } sign\frac{\partial D}{\partial\varepsilon} < 0 \tag{13}$$

We now turn to the interpretation of the previous results. First, as regards (9) and (10), we get that, while an increase in w_P (keeping all other variables constant) implies that that more individuals get educated (smaller θ^*), a rise in w_T leads to the opposite effect. Obviously, these two effects arise from the assumed relationship between type of contract and educational level. Since a P contract is only offered to highly-educated individuals, a higher wage in this type of jobs necessarily induces a greater incentive to invest in education. Conversely, a rise in the temporary workers' wage makes P jobs and education less attractive.

Secondly, as can be observed in (11), the effect of changes in severance pay F over θ^* depends on the business-cycle phase. If ε is sufficiently large (i.e., when the economy suffers a recession) then an increase in F reduces θ^*, so that more individuals invest in education. The opposite occurs when ε is small, (i.e., when the economy enjoys an expansion). The intuition underlying this result stems from the two effects that severance pay has on the asset value of educated workers in P jobs, as illustrated in (5). When F goes up, the first effect is that, for given w_P, the expected surplus of a worker who is not dismissed (i.e., $w_P - F$ times the probability of keeping the job) decreases. This implies that jobs with P contracts, and therefore education, become less attractive choices. The second one is the direct and positive effect for workers of an increase in F in case of dismissal, which makes these jobs more attractive by providing higher severance pay.

When the economy enters a recession, the second effect becomes more relevant since the probability of losing a job is greater. As a result, an increase of F encourages workers to invest in education. The opposite occurs during a boom, in which the probability of getting dismissed is lower, so that a rise in F reduces the surplus obtained by the worker in a P job and thus decreases the incentives for education.

Thirdly, a very relevant phenomenon in the Spanish economy, such as the construction boom, can be interpreted in this model as a drop in q because temporary jobs last longer on average as a result of higher demand for this type of jobs. Therefore, as T contracts become more attractive, (12) implies that θ^* increases unambiguously, and therefore workers invest less in education.

Finally, (13) illustrates the direct effects of the business cycle on education. It can be seen how in a period of high growth, i.e., when ε falls, θ^* increases (less workers invest in education) and the opposite holds in a recession. Therefore, following the same reasoning as for the effects of F on θ^*, investment in education shows a clearly counter-cyclical pattern.

DATASET AND VARIABLES

The population of interest is defined as those individuals participating in PIAAC aged 16 to 65 who have the status of employees at the time of the survey. Out of the 6055 individuals who responded fully to the questionnaires in PIAAC, the sample size is reduced to about 2500 individuals who meet the above-mentioned requirements.

Our main control variable, *temporary contract*, is a dichotomous (dummy) variable that takes the value 0 when the individual has a permanent contract and value 1 when the contract is a temporary one (i.e., fixed-term contracts, temporary employment with an employment agency, or some kind of training contracts).

As argued earlier, our empirical approach focuses on first analyzing how the type of contract, affects OJT activities in the firm to next testing how training impinges on the employees' literacy and numeracy skills according to the scores available in the PIAAC database. Both the illustrative model and the related literature suggest that temporary workers in highly dual labour markets tend to accumulate less human capital than workers with permanent contracts. This could be due to demand and supply. As regards demand, temporary workers have lower incentives to get trained because, due to the low temp-to-perm conversion rates, this does not help them to reach stable jobs. With regard to supply, firms invest less in the specific human capital of their temporary workers because they anticipate that the short duration of this type of contract does not make it profitable to invest in their workers. To empirically evaluate this prediction, we use two proxies of specific human capital accumulation at the workplace. Firstly, we use a dummy variable, D^{OJT}, which takes the value 1 if the worker claims to have attended a training session organized in the workplace or provided by their supervisors or colleagues in the past 12 months, and 0 otherwise. According to PIAAC, these training sessions should be characterized "by planned periods of training, instruction or practical experience, using the normal methods of work." They include, for example, "training or instruction courses organized by the directors, managers or colleagues to help the respondent to do their job better or to familiarize them with their new tasks."

While the D^{OJT} dummy variable is an indicator of training activities within the firm, it does not accurately reflect the intensity of these activities. To address this shortcoming, we use additionally the number of training activities which the worker has attended during the past 12 months, n^{OJT}. It should be noted that, in accordance with the design of the survey, the respondent should count all training tasks that are interrelated as a single activity, even if they have taken place on different days,. The essential feature of each activity is that it should be designed "to facilitate the adaptation of personnel to a particular set of new competences". Therefore, the variable n^{OJT} reflects the intensity of investment in new competences regardless of their level of difficulty or the time that has been devoted to each one of them. [1]

In line with our theoretical predictions we will show that, in general, temporary workers receive less OJT than those with permanent contracts. Yet, an interesting feature which has not been explicitly considered in our model is that, despite receiving less training, temporary workers may not perceive this as a problem since their skills requirements on these jobs tend to be low in general. The PIACC database allows us to explore this issue through the availability

[1] PIAAC also provides a subjective measurement that reflects to some degree the intensity with which the worker acquires new skills in the job. In the survey, workers are asked to indicate, approximately, the frequency with which their job involves learning new skills. Besides the problem of interpretation often encountered with such subjective statements, this variable does not have enough variation to be really informative: over 90% of respondents reply that their job involves learning new skills "at least once a month." For these reasons, we have decided to discard it in this study.

of a subjective measure of workers' demand of higher OJT. In particular, we use a dummy variable, denoted as $more^{OJT}$, which takes the value 1 if the worker claims that he/she needs more training to perform his/her job tasks properly, and 0 if otherwise.

It is plausible that differences in the training processes within the firm generate differences in workers' promotion opportunities workers to better contracts. However, the extent to which these differences in human capital accumulation could lead to differences in general human capital that the worker could use in other firms remains an open question. To address this issue, we analyze the effect of OTJ activities on the two measurements of general cognitive skills reported in the Spanish PIAAC sample, namely, the scores achieved on the literacy and numeracy tests.

Table 1.1 presents the main descriptive statistics of the main outcome variables in the subsequent empirical analysis, i.e., the availability and intensity of OTJ activities, the perception on the efficacy of the training process and, finally, the scores in both tests.

Table 1.1. Descriptive Statisitics (PIAAC)

Panel A	**No. Obs.**	**Pop. 16- 65 years[(a)]**	**Employed[(a)]**	**Employees[(a)]**	
PIAAC sample	6055				
Sample with ages between 16 and 65 years old	5954				
Type of workers	3060	53.18			
Self-employed	547	9.41	17.69		
Employee	2513	43.77	82.31		
Temporary	589	9.71	18.26	22.18	
Panel B	Training and abilities by type of contract[(a)]		Difference (%)	Stand. Dev.[(b)]	P-value
	Permanent	**Temporary**			
Percentage of employees with training activities	48.43	31.81	16.62 (52.25)	2.35	0.000
Average number of activities	2.85	2.33	0.52 (22.32)	0.29	0.073
Percentage which believes it needs training	39.55	35.42	4.13 (11.66)	2.48	0.096
Index of literacy[(c)]	262.68	255.63	7.05 (2.76)	2.10	0.001
Index of numeracy [(c)]	260.94	246.81	14.13 (5.73)	2.00	0.000
	D^{OJT}=1	D^{OJT}=0			
Index of reading literacy [(c)]	268.89	254.69	14.2 (5.58)	1.51	0.000
Index of numeracy [(c)]	268.09	249.44	18.65 (7.48)	1.49	0.000

Notes: A worker has a temporary contract when he/she has a fixed-term contract, a temporary job with a temporary work agency or any type of training contract. D^{OJT} takes the value 1 when the worker claims to have attended training activities in the last 12 months, and 0 in the opposite case. The indices of *literacy* and *numeracy* are measurements attributed from the responses to exercises which are part of the survey. *Literacy* measures the ability to understand and use texts (written or in a digital format) in different contexts, while *numeracy* measures the use, application, interpretation and communication of mathematical information and ideas.
[(a)] Percentages of population estimated using weights of the whole sample as weightings.
[(b)] Using the replication method JK1.
[(c)] Using the attributed value 5.

The results of Table 1.1 are fairly consistent with the basic predictions of the model. As can be observed, temporary workers undertake less training activities than permanent workers. This finding is robust both in the *extensive margin* (i.e., using D^{OJT} as a measure of the availability of training) and the *intensive margin* (i.e., using n^{OJT} as a measure of the intensity of training). Further, in line with our previous conjecture, the results for $more^{OJT}$ suggest that the reduced OJT of temporary workers does not translate into a greater demand of extra training. Finally, both literacy and numeracy scores are significantly lower among temporary workers.

However, it is important to stress that the negative relationship found between temporary contracts and OTJ activities does not necessarily imply causality. In particular, the results in Table 1.1 do not allow us to state that workers accumulate less specific human capital in the firm because their contract is a temporary one. The fundamental reason for why this may be a misleading conclusion is that both the type of contract and training activities could be, in general, jointly affected by other variables. For example, consider a worker with a high level of motivation to perform well in the job. Then, precisely because of this feature, this individual could influence his/her employer to obtain a permanent contract and freely choose to participate intensively in OJT activities. In that case, we would observe a positive correlation between having a permanent contract and a high intensity of training activities but the intense process of accumulating specific human capital would be the result of the high motivation of the individual, not of holding a permanent contract. To avoid such confounding issues in our analysis, it is essential to control for all potential factors which simultaneously affect the respective outcome variables (i.e., both variables related to training activities as well as the skills competence variables) and the treatment variable (in our case, the type of contract).

To do so, in the the next section we present the estimates of several econometric models which include two types of controls. First, we use the individuals' basic characteristics such as age, gender, educational attainment, marital status, whether they have children, whether they are immigrants and the parental educational background. In addition, we will also control for a potentially key variable which often is not available in other datasets but which PIAAC reports. This is the degree of motivation of the worker, measured by a dummy variable, denoted as *motivation*, which takes the value 1 when the individual claims to feel identified "to a great extent" or "to a very great extent" with learning new skills, with working out difficult tasks, with relating new things to what they already know, and with seeking more information when they do not understand something". Secondly, in some specifications we also control for occupational dummies (as measured by the ISCO08 classification to two digits) and industry dummies (as measured by the one-digit classification from the fourth ISIC revision).

RESULTS

The first set of results is reported in Table 1.2. They are expressed in terms of marginal effects and correspond to the estimation by maximum likelihood of a *probit* model to explain the probability of receiving training at the workplace (D^{OJT} = 1) depending on our explanatory variable of interest, *temporary contract*, and on other types of controls. In column [1], we present the results in the case when the type of contract is the only covariate in the *probit* model. In column [2], job tenure, worker's age and its square (as a proxy for potential experience, given the higher educational level reached), gender (female = 1) and educational level (with a low level as the reference category) are included as additional regressors. In column [3], the previous group of controls is extended by also including dummy variables of the parents' educational level, marital status, immigrant status and the degree of motivation of the worker. Finally, in column [4], dummy variables of sector/industry and occupation are also added, thereby constituting the more general specification of the *probit* model. For convenience, this ordering by columns, from the most restrictive specification to the most general, is kept for the rest of Tables presented in this section. It is also important to note that the number of observations used in the different regression specifications varies slightly because some controls are not available for all individuals analyzed in the larger samples.

The main result in Table 1.2 is that, in line with our main hypothesis, the estimated coefficient on the "*temporary contract*" dummy variable is negative and statistically very significant in all specifications,. Furthermore, the estimates suggest that the marginal effect is quantitatively very relevant. In the absence of further controls (column [1]) , having a temporary contract is associated with a reduction in the probability of receiving OTJ of 16.4 percentage points (pp.), where the unconditional probability of receiving OTJ among permanent workers is 43.7%. By progressively adding further controls, the estimated marginal effect is halved, falling to about 8-9 percentage points, a result which is fairly robust across columns [2] to [4]. Therefore, one can infer from this evidence that the detrimental effect of contractual instability on the specific training received in the workplace is sizeable. For example, the marginal effect in the specification with all of the controls (reported in column [4]) implies that for the typical worker with a permanent contract, switching to a temporary contract reduces the probability of receiving training at the workplace by 18 % (= -0.08/.44).

With respect to the other controls, it is worth pointing out that a higher educational level increases the probability of receiving OJT and also that that probability also increases with age up to a threshold of about 30 years due to the concave shape of the quadratic polynomial for this variable. Furthermore, although statistically less significant than the above-mentioned estimates, there is evidence about women having a lower probability of OJT, although this gender effect disappears as the number of controls in columns [3] and [4] is extended. In this regard it should be pointed out that another variable (not reported in Table 1.2) which has been included in all the specifications is whether the individual has a part-time job (where the reference category is full-time work). Its inclusion did not change any of the previous results, either in this Table or in any of those shown further below, but it did cancel out the above-mentioned gender effect. This is probably explained by the high incidence of part-time working schedules among female employees, making it impossible to identify whether the relevant covariate is gender or working part time. Finally, although not reported in order to save space, the variables of immigrant status and motivation proved to be significant in columns [2] and [3], with negative and positive signs, respectively. However, unlike what happens with the covariate *temporary contract*, the effect of *motivatio*n becomes weaker on adding the set of occupational and industry dummy variables.

Table 1.2. Probit Model (Marginal Effects). Dependent variable: DOJT

	[1]	[2]	[3]	[4]
Temporary contract	**-0.1636*** **	**-0.0923*** **	**-0.0795*** **	**-0.0795*** **
	(0.0223)	**(0.0265)**	**(0.0284)**	**(0.0306)**
Job tenure	---	0.0053***	0.0049***	0.0035**
		(0.0014)	(0.0015)	(0.0016)
Age	---	0.0132*	0.0179**	0.0150*
		(0.0071)	(0.0084)	(0.0088)
(*Age*) ^{2} / 100	---	-0.0002**	-0.0002**	-0.0002**
		(0.0001)	(0.0001)	(0.0001)
Woman	---	-0.0359*	-0.0376*	-0.0117
		(0.0205)	(0.0219)	(0.0270)
Middle educational level	---	0.1279***	0.1359***	0.0947***
		(0.0286)	(0.0305)	(0.0329)
High educational level	---	0.2731***	0.2550***	0.1578***
		(0.0227)	(0.0258)	(0.0328)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2503	2501	2258	2206
Pseudo R-sq.	0.015	0.065	0.074	0.102
Prob. obs.	0.4371	0.4374	0.4353	0.4424

Note: The marginal effects of the dichotomous variables are calculated as the change of the estimation of the probability when the variable changes from 0 to 1. The *temporary contract* variable is a dichotomous variable which takes the value 0 when the individual has a permanent contract and 1 when he/she has a temporary contract. *Job tenure* measures the duration of the current job. *Middle educational level* is a dichotomous variable which takes value 1 when an individual has vocational training at an intermediate level, the baccalaureate, or old higher baccalaureates and pre-university courses. *High educational level* takes a value of 1 when the individual has a tertiary education degree. The variables about the educational level of the parents are dichotomous variables for the three levels of education. *Civil status* reflects whether the individual is married, *children* reflects whether they have children, and *immigrant* reflects whether the individual was born in this country. The *motivation* variable takes the value 1 when the individual claims to feel "greatly" or "very greatly" identified with the learning of new skills, working out difficult tasks, relating new things to what they already know, and looking for information when they don't understand something. The variables of *occupation* are obtained with the ISCO08 to two digits while the variables of *sector* are obtained with the one-digit classification from the fourth ISIC revision.
Levels of significance: * p<0.10, ** p<0.05, *** p<0.01

We next report In Table 1.3 the results from estimating the coefficients of a count data model based on the *Negative Binomial* distribution (this distribution is used after rejecting the equality of mean and variance implied by the more restrictive *Poisson* distribution), in order to detect the discrete nature of the dependent variable, namely, the number of training activities which the worker has attended over the past 12 months, n^{OJT}. The results for our variable of interest, *temporary contract*, are similar to those obtained in Table 1.2, in the sense that this covariate systematically exhibits a negative sign, indicating again that holding a temporary contract reduces the number of OJT activities. However, unlike what happened in the *probit* model for D^{OJT}, the estimated coefficients of this variable are no longer statistically significant and become smaller as the range of further controls s increased. This may be because the number of individuals who report this information (around 1000) represent less than half the sample size used in the *probit* model.

Table 1.3. Binomial Negative Model (Coefficients). Dependent variable: nOJT

	[1]	[2]	[3]	[4]
Temporary contract	**-0.1399****	**-0.1266***	**-0.0845**	**-0.0399**
	(0.0712)	**(0.07714)**	**(0.0884)**	**(0.0899)**
Job tenure	---	0.0076*	0.0052	0.0049
		(0.0039)	(0.0041)	(0.0043)
Age	---	-0.0152	-0.0417*	-0.0109
		(0.0193)	(0.0231)	(0.0236)
$(Age)^2/100$	---	0.0066	0.0401	0.0043
		(0.0239)	(0.0277)	(0.0281)
Woman	---	-0.0144	-0.0367	-0.1367**
		(0.0543)	(0.0576)	(0.0657)
Middle educational level	---	0.0574	-0.014	-0.0645
		(0.0846)	(0.0900)	(0.0923)
High educational level	---	0.2234***	0.0954	0.0094
		(0.0688)	(0.0769)	(0.0906)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
Dispersion Coefficient	-0.8518***	-0.8766***	-0.8999***	-1.1637***
	(0.0689)	(0.0695)	(0.0736)	(0.0823)
No. obs.	1092	1092	981	974
Pseudo R-squared	0.001	0.005	0.015	0.056

Note: The variable n^{OJT} measures the number of training activities which the worker has attended in the last 12 months. See the note from Table 1.2 for the definition of the controls.
Levels of significance: * p<0.10, ** p<0.05, *** p<0.01

Finally, in Table 1.4 we report the results of estimating another *probit* model, this time applied to explaining the probability associated with the dummy variable on the need for a higher level of training, $more^{OJT}$. Although the estimated marginal effect on the *temporary contract* variable is negative in all cases, it is statistically significant only in column [1]. In agreement with what was argued in the previous section, this lack of statistical significance could be due to the fact that some of the additional controls (especially the educational level or the dummies of occupation and sector) may be detecting the potential mismatch between the training of the individual and the job requirements in a much more accurate way than the type of contract the individual holds.

Table 1.4. Probit Model (Marginal Effects). Dependent variable: moreOJT

	[1]	[2]	[3]	[4]
Temporary contract	**-0.0532****	**-0.0106**	**-0.0168**	**-0.0175**
	(0.0225)	**(0.0260)**	**(0.0276)**	**(0.0295)**
Job tenure	---	0.0016	0.002	0.0011
		(0.0013)	(0.0014)	(0.0015)
Age	---	0.0210***	0.0201**	0.0215***
		(0.0067)	(0.0080)	(0.0083)
$(Age)^2 / 100$	---	-0.0003***	-0.0003***	-0.0003***
		(0.0001)	(0.0001)	(0.0001)
Woman	---	-0.0209	-0.0251	0.0126
		(0.0197)	(0.0210)	(0.0259)
Middle educational level	---	0.0807***	0.0749**	0.0483
		(0.0282)	(0.0300)	(0.0319)
High educational level	---	0.1588***	0.1492***	0.0685**
		(0.0228)	(0.0257)	(0.0321)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2508	2506	2262	2235
Pseudo R-sq.	0.002	0.023	0.025	0.071
Prob. obs.	0.3792	0.3795	0.382	0.3834

Note: The marginal effects of the dichotomous variables are calculated as the change in the estimate of the probability in the caseof a change of the variable from o to 1. The variable $more^{OJT}$ takes the value 1 if the worker claims to need more training in order to properly perform his/her work tasks and 0 if otherwise. See the note from Table1.2 for the definition of the controls.
Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

A brief summary of the evidence reported so far indicates that the *temporary contract* treatment variable has a systematically negative effect on the three outcome variables we have analyzed. Moreover, the finding that this effect is robust to model specification and statistically significant only when the dependent variable is D^{OJT} may be due to the lower measurement error of this outcome variable than the other two.

In view of these results, the next step is to check whether the availability or the intensity of OJT activities has an effect on the scores obtained by the individuals in the *literacy* and *numeracy* tests. Tables 1.5 and 1.6, respectively, present the results derived from estimating a linear regression model by OLS, where the outcome variables are the scores and the variables of interest are the two measurements of OJT for which a greater effect of temporary contract has been found, namely D^{OJT} , and to a lesser extent, n^{OJT}. Note that in both models the *temporary contract* treatment variable is not included as a regressor in order to test if the effect of this variable on the scores is mainly brought about through the amount of OTJ received at the workplace, and not directly.

Tables 1.5 and 1.6 present the estimated coefficients in a regression where the dependent variable is *literacy* and *numeracy*, respectively. Columns [1] and [2] in both Tables differ in that D^{OJT} is used as a regressor in the first column while n^{OJT} is used in the second column. As can be observed, the results indicate that both variables have a positive effect on scores in the PIAAC tests, except in the last column of Table 1.5. Furthermore, this effect tends to be stronger and statistically more significant in Table 1.6, when examining the relationship between D^{OJT} and *numeracy*. So, from the comparison of the estimates in both Tables with the raw differences reported in Table 1 between the PIAAC scores achieved by employees with and without OJT (14.2 pp. in *literacy* and *18.6* pp. in numeracy), we get that, *ceteris paribus*, the availability of such specific training activities account for 15 % (2 pp.) and 28% (5 pp.) of the raw score gaps in *literacy* and *numerac*y, respectively.

Therefore, our evidence suggests that training at the workplace and, to a lesser extent, the intensity of this training improves the cognitive skills of the workers. In order to check if the effect is mainly due having a temporary contract, this covariate was also added to the previous specifications, together with the two training variables. The main result that we find (not reported in the Tables) is that the coefficient on *temporary contract* is never significant and the estimated coefficients on D^{OJT} and n^{OJT} hardly experience any significant changes. Thus, we conclude that OJT plays an important role in explaining the PIAAC scores.

Table 1.5. Ordinary Least Squares (Coefficients).. Dependent variable*: literacy* scores

	[1]	[2]	[3]	[4]
D^{OJT}	**3.5467****	---	**2.072**	**1.2566**
	(1.5939)		**(1.6009)**	**(1.6095)**
n^{OJT}	---	**0.5380****	---	---
		(0.2557)		
Job tenure	0.2672**	0.3766**	0.1667	0.0734
	(0.1059)	(0.1727)	(0.1085)	(0.1119)
Age	2.6996***	2.6412***	3.4779***	3.6443***
	(0.5096)	(0.8166)	(0.5709)	(0.5850)
$(Age)^2 / 100$	-4.2135***	-4.1243***	-4.9442***	-5.1794***
	(0.6347)	(1.0341)	(0.6886)	(0.7046)
Woman	-9.2612***	-7.8979***	-7.4145***	-9.7869***
	(1.5476)	(2.3168)	(1.5449)	(1.9085)
Middle educational level	24.1234***	24.1112***	21.7160***	17.6391***
	(2.2114)	(3.6625)	(2.2112)	(2.3179)
High educational level	45.3710***	45.8212***	36.8107***	24.6992***
	(1.8098)	(2.8883)	(1.9208)	(2.2671)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2807	1162	2536	2475
R-sq.	0.250	0.219	0.295	0.327

Note: Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

Table 1.6. Ordinary Least Squares (Coefficients). Dependent variable: *numeracy* scores

	[1]	[2]	[3]	[4]
D^{OJT}	**7.4523*** **	---	**5.7716*** **	**3.7712** **
	(1.6198)		**(1.6325)**	**(1.6500)**
n^{OJT}	---	**0.3888**	---	---
		(0.2555)		
Job tenure	0.3878***	0.3854**	0.2628**	0.1511
	(0.1055)	(0.1728)	(0.1094)	(0.1135)
Age	2.5632***	3.1910***	3.1082***	3.2456***
	(0.5295)	(0.8415)	(0.5917)	(0.6103)
$(Age)^2 / 100$	-4.1618***	-4.8786***	-4.6634***	-4.8173***
	(0.6566)	(1.0565)	(0.7117)	(0.7327)
Woman	-16.9921***	-14.6935***	-16.3784***	-16.4630***
	(1.5759)	(2.3156)	(1.5976)	(1.9500)
Middle educational level	25.9530***	27.3051***	23.1693***	18.6021***
	(2.2359)	(3.6899)	(2.2672)	(2.4043)
High educational level	48.1732***	48.5652***	39.9913***	27.4181***
	(1.8621)	(3.0138)	(1.9874)	(2.3328)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2807	1162	2536	2475
R-sq.	0.288	0.247	0.322	0.35

Note: See the notes of Tables 1.1 and 1.2 for definitions of the variables.
Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

Finally, Tables 1.7 (dependent variable: *literacy*) and 1.8 (dependent variable: *numeracy*) report the estimated coefficients obtained from the reduced forms of the previous models in which the two training variables considered previously are now replaced by the *temporary contract* covariate, to which the remaining the set of controls are gradually added. The idea of these reduced forms is that if the mechanism we explore is valid, we should expect a negative effect of this treatment variable on the s PIAAC scores. In other words, *ceteris paribus*, being a temporary worker has a negative effect on the scores mainly through the reduction of the amount of OJT provided at the workplace and not so much through other alternative channels. The results show a certain degree of support for this hypothesis, since the coefficient on the "*temporary contract*" variable is always negative, albeit it only turns out to be statistically significant in the case of *numeracy* (with the exception of column [4]).

Table 1.7. Ordinary Least Squares (Reduced Form). Dependent variable: *literacy* scores

	[1]	[2]	[3]	[4]
Temporary contract	**-6.5503*****	**-4.0915***	**-2.9321**	**-2.0831**
	(2.2086)	**(2.1914)**	**(2.1618)**	**(2.2537)**
Job tenure	---	0.2758**	0.1982*	0.0748
		(0.1174)	(0.1204)	(0.1236)
Age	---	3.2708***	3.6018***	3.5278***
		(0.5666)	(0.6226)	(0.6257)
$(Age)^2 / 100$	---	-0.0479***	-0.0511***	-0.0505***
		(0.0070)	(0.0075)	(0.0075)
Woman	---	-8.3752***	-7.2715***	-9.6194***
		(1.6260)	(1.6280)	(1.9786)
Middle educational level	---	22.3422***	21.6332***	17.4162***
		(2.3669)	(2.3380)	(2.4210)
High educational level	---	42.0032***	37.3696***	24.7004***
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2513	2447	2266	2244
R-sq.	0.003	0.262	0.291	0.321

Note: See the notes of Tables 1.1 and 1.2 for definitions of the variables.
Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

Table 1.8. Ordinary Least Squares (Reduced Form). Dependent variable: *numeracy* scores

	[1]	[2]	[3]	[4]
Temporary contract	**-12.5522*** **	**-4.5196** **	**-3.668***	**-2.5884**
	(2.2851)	**(2.2124)**	**(2.2375)**	**(2.3210)**
Job tenure	---	0.3751***	0.2631**	0.1115
		(0.1190)	(0.1217)	(0.1253)
Age	---	3.2379***	3.4562***	3.4258***
		(0.5779)	(0.6392)	(0.6438)
$(Age)^2 / 100$	---	-0.0486***	-0.0509***	-0.0503***
		(0.0071)	(0.0077)	(0.0077)
Woman	---	-15.8232***	-15.6563***	-15.7823***
		(1.6537)	(1.6757)	(2.0082)
Middle educational level	---	23.6664***	22.8811***	18.3916***
		(2.3976)	(2.3863)	(2.4894)
High educational level	---	44.2566***	40.2667***	27.2830***
		(2.0353)	(2.0713)	(2.3874)
Educational level of parents	No	No	Yes	Yes
Civil status, children	No	No	Yes	Yes
Immigrant	No	No	Yes	Yes
Motivation	No	No	Yes	Yes
Dummies by Sector and Occupation	No	No	No	Yes
No. obs.	2513	2447	2266	2244
R-sq.	0.012	0.289	0.313	0.345

Note: See the notes of Tables 1.1 and 1.2 for definitions of the variables.
Levels of significance:.* p<0.10, ** p<0.05, *** p<0.01

In sum, the results presented in this section are, in general, consistent with the basic prediction of our model. Temporary workers are significantly less likely to engage in OJT activities at the workplace that workers with a permanent contract, even after controlling for a large number of individual and job characteristics including workers' motivation. By contrast, workers with temporary contracts do not seem to differ from workers with permanent contracts in their perceptions regarding the appropriateness of their training with respect to the skills requirements in their current jobs. Finally, both the scores on literacy and numeracy skills are significantly lower for workers who do not receive any type of training. Moreover, among those who receive OJT, the scores are lower for those who receive less training.

CONCLUSIONS

We began this study by observing that the Spanish economy has been characterized in the last two decades by its extremely dual labour market and its low TFP growth. On that basis, our goal is to analyze how the gap in firing costs between permanent and temporary workers may have affected a relevant determinant of TFP growth, as is the amount and quality of the firm-provided training that workers receive at the workplace.

To address this issue, by means of a simple theoretical model we first illustrate the mechanism linking labour-market dualism to the deficiency in the training of temporary workers. We show that, in a context where wages are not flexible enough and the firing-costs gap between permanent and temporary workers is too high, firms are less inclined to convert unstable contracts into stable ones. In these circumstances, firms have few incentives to invest in the training for temporary workers, while the latter also lack the incentives to improve their performance through exerting more effort at the workplace.

The cross-sectional database for Spain provided by PIAAC allows us to explore how the widespread use of temporary contracts may have affected the willingness of firms to provide specific OJT to their workers and how the lack of this type of training may have negatively affected the specific human capital of the latter. Specifically, the availability of several different training measures at the workplace, as well as workers' scores on literacy and numeracy tests, allows us to check, firstly, the direct relation between the type of contract held by workers and the amount of OJT they receive and, secondly, whether this type of training affects both literacy and numeracy skills of the workers.

We present econometric results for several outcome variables: two measures of training activities (availability and intensity), a measure of workers' perceptions on the need of greater and better OTJ, and two measures of cognitive skills. For each econometric model, we report results using different specifications. In our broader specification we consider (in addition to the *temporary contract* indicator) a wide set individual and job characteristics, including proxy variables of the workers' family background, ability and motivation.

Our main empirical findings do not contradict and, in general, support our basic hypotheses that there is a negative relationship between job insecurity and training at the workplace, as well as a positive relationship between the amount of OJT activities and workers' cognitive skills. To the extent that an improvement in the educational levels of the Spanish population is a *sine qua non* condition for improving welfare through increased competitiveness in technologically-advanced sectors, reducing the excessive segmentation of the Spanish labour market seems to be an essential policy measure.

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APPENDIX

(Integration by Parts)

Let $R = w_P - F$

$$W_P(\varepsilon,\zeta) = \zeta + \left[\int_{\bar{\zeta}(1-\varepsilon)}^{\bar{\zeta}} \max(\zeta - w_P, -F)\, dG_\zeta(\varepsilon) \right] =$$

$$= \zeta + \left[\int_{\bar{\zeta}(1-\varepsilon)}^{\bar{\zeta}} \max(\zeta - w_P + F, 0)\, dG_\zeta(\varepsilon) - F \int_{\bar{\zeta}(1-\varepsilon)}^{\bar{\zeta}} dG_\zeta(\varepsilon) \right]$$

$$= \zeta + \left[\int_{\bar{\zeta}(1-\varepsilon)}^{\bar{\zeta}} \max(\zeta - w_P + F, 0)\, dG_\zeta(\varepsilon) - F \right]$$

$$= \zeta + \left[\int_{R}^{\bar{\zeta}} (\zeta - w_P)\, dG_\zeta(\varepsilon) + F \int_{R}^{\bar{\zeta}} dG_\zeta(\varepsilon) - F \right]$$

$$= \zeta + \left[\int_{R}^{\bar{\zeta}} (\zeta - w_P)\, dG_\zeta(\varepsilon) - F G_\zeta(R) \right]$$

Then, using integration by parts for $\int_{R}^{\bar{\zeta}} (\zeta - w_P)\, dG_\zeta(\varepsilon)$ yields

$$= \zeta + \left[(\bar{\zeta} - w_P) - (R - w_P) G_\zeta(R) \right] - \int_{R}^{\bar{\zeta}} G_\zeta(\varepsilon)\, d\zeta - F G_\zeta(R) =$$

$$= \zeta + (\bar{\zeta} - w_P) - \int_{R}^{\bar{\zeta}} G_\zeta(\varepsilon)\, d\zeta$$

where the last equality follows from $(R - w_P) G_\zeta(R) = -F G_\zeta(R)$.

2. Estimating the influence of schooling on the PIAAC competencies

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2. ESTIMATING THE INFLUENCE OF SCHOOLING ON THE PIAAC COMPETENCIES[1]

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ABSTRACT

The objective of this study is to estimate the effect of Spanish post-compulsory schooling on the competencies measured in the PIACC. This effect has a certain political interest, since its scale will shed light on how severe are problems such as "early school dropout" are and how efficient are the solutions to them. People with more years of schooling have higher PIACC scores, but it is partly because post-compulsory education selects the most competent students. In order to properly identify each effect, it would be necessary to measure competencies before and after schooling. With a single assessment, which is what PIACC provides, we need to find situations where we can separate the selection effect from the actual effect. Here we have examined two of these situations. One is that of older ages cohorts, whose years of schooling we assume increased regardless of their competencies. The other one is that younger groups competencies appear to have developed before post-compulsory education. Throught the first procedure, we found that one year of schooling of indefinite level increased the PIACC literacy score by 5 points, equivalent to more or less 0.12 SD. With the second procedure we found that a year of post-compulsory education increased PIACC literacy at the most by 2 points, 0.05 SD, and most likely by a lot less. These differences suggest that elementary education has a greater effect than non-compulsory education, but the PIACC data do not allow this to be confirmed directly.

[1] I wish to thank Miguel Caínzos for his suggestions for the first version, which improved considerably thanks to them.

Keywords

Literacy determinants, school efficacy.

INTRODUCTION

Studies on literacy began in the United States more or less at the same time as school evaluations, using the same type of tests, produced by the *Education and Testing Service* (Sticht and Armstrong, 1994). Soon the concept of *literacy* was extended so that, aside from its strict sense (knowing how to read and write), it also included the use of information in everyday life (functional literacy). Thus, all studies conducted since the 80s are based on the definition of the *Young Adult Literacy Survey* conducted in the United States in 1986: “using printed and written information to function in society, to achieve one's goals, and to develop one's knowledge and potential”.

As highlighted by the presenters of the *National Adult Literacy Survey* of 1993, this definition “goes far beyond simple decoding and comprehension to include a wide range of skills that adults use when doing many different types of tasks at work, home and in the community” (Lynn and Baldi, 1993). This implies recognising that, unlike literacy in its strict sense, which is a task pertaining to schools, these skills are learnt in the same contexts where they are carried out, as well as in school. This has been pointed out by the OECD, for example in the successive PISA (*Programme for International Student Assessment*) reports:

“Literacy is no longer considered an ability acquired only during childhood in the first years of school. Rather, it is seen as a set of knowledge, skills and strategies that individuals build through their life in various contexts, through interaction with their peers and with the community”. (OECD, 2010:25).

The OECD does not retreat before the immediate consequence that schools should not be assessed by this “literacy” in a broad sense, which spreads far beyond its functions. As already written in the first PISA report:

“If one country’s reading, scientific or mathematical literacy is significantly higher than another country’s, we cannot automatically infer that the schools or other elements of the education system in the former country are more effective than those of the second one”. (OECD, 2003:249).

These viewpoints are confirmed in the PISA reports themselves, which have found very few variables influencing the results of the tests at school and system.level.

However, not only does literacy) depend to an uncertain extent on schools, but schooing itself also depend on literacy. Thus, when highlighting the importance of the competencies assessed in PISA, the promoters of the project insist, rightfully so, on their influence on subsequent educational paths, as confirmed by the follow-up of students conducted in Canada (Gluzinsky and Bayard, 2010; Shipley and Gluzinsky, 2012; Hansen and Liu, 2013). In contrast, results derived from international literacy studies (e.g. OECD and Statistics Canada, 2000) underline their dependence on schools, without taking into account the reverse relationship.

Therefore it seems important to address the question of how much people *literacy* actually depends on the years they spend in school. The extended concept of literacy just described suggests that the first years of school are the most important ones, and that subsequent years have a decreasing impact and soon become irrelevant. This hypothesis seems especially appropriate for reading comprehension. After a few years of schooling, most students are capable of decoding written texts and oral language, and after a few more they have had the opportunity to practice these skills with all type of texts, both in school and outside. It does not appear that this reading competency can increase with more years of schooling, taking into account that reading is an activity embedded in most social contexts and interactions of the modern world. Although perhaps less strongly, this argument could be applied to most of the activities scoring in the PIACC numeracy test.

I have found some support of this hypothesis in literature. A lot of research on intelligence tests gives results consistent with its. For example, Cahan and Cohen, 1989, found that in Israel 5th Grade has a greater influence than the tenth year of lifel; and in this same sense could be interpreted Ceci's review of the literature(1991). However there are also studies that have found influence of school on Intelligence Quotient (IQ) in adolescence. In the United States, the NLSY data analysis has produced positive estimates, some very low ones (Hernnstein and Murray, 1995), but also as high as 0.3 SD (Winship and Koremnan, 1997; Hansen, Heckman and Mullen, 2004; Cascio and Lewis, 2006). In Norway, Brinch and Galloway (2012) found that a comprehensive reform introduced in the sixties increased the average duration of schooling by 0.16 years and IQ by 0.60 points (that is, 3.7 points for every additional year of school, or nearly 0.25 SD). They concluded that school increases IQ in adolescence.

The influence of school years on IQ tests can be considered the lower limit of that same influence on achievement tests such as PISA and PIACC, as they depend more on cultural contents than the former, even then those measuring "crystallised" IQ. Resorting to IQ is justified by the proximity of what is measured by both types of tests, as already noted long ago by Jencks (Jencks, 1972) and continuously repeated by others (Godfredson, 2003). I have not been able to find many studies made directly with *literacy* tests. I only have references of Reder's (1998) with NALS data. Reder himself (2012), following an adult sample for ten years, found slight improvements among those following literacy programmes, but also among those who did not. Walsh (2012) found parabolic effects in the NAEP tests: a year of kindergarten produces 1/3 of SD, completing 4th Grade produces 1.5 SD, finishing 8th however only 0.5 SD, but the figures seem excessive. Grenier et al (2008) analysed a *Statistics Canada* survey designed to find the reasons for low literacy. Their conclusion was that differences in vocabulary and the ability to decode explained the differences between the lowest level and the rest, but not the differences between the medium and high levels, which they attributed to differences in reading strategies. My own analysis of the PISA data comes to the conclusion that the tenth year of school has no influence on the Science score at age fifteen (Carabaña, 2008:82).

This paper reports an attempt to confirm this hypothesis of the diminishing effect of the years of school on the competencies measured in achievement tests, which henceforth we shall resign ourselves to limit to literacy. The main result found is that the efficacy of school is very small or nil after Elementary Education. Sso we cannot expect our Secondary Schools or our Universities to raise literacy among the population much. The paper now moves on to the methodology, continues with the results and ends with some considerations on it all, before trying to reach some conclusions.

DATA, METHODS, VARIABLES

Data

We used the PIAAC data for Spain, 2012. We limited the study to people PIAAC defined as "native-born", which left a sample of aprox. 5150 people, depending on the cases lost in each variable.

Methods

It is well known that people with more years of school have higher scores in all type of cognitive ability tests, and those used in adult literacy studies are no exception[2]. Part of this correlation is due to the fact that continuing in school after compulsory education depends on student academic ability, in general because students choose based on their abilities, and in particular due to explicit selection procedures in certain schools. In an equation such as:

$$PLP_i = a + bS_i + e \ (1),$$

where PLP represents the PIAAC Literacy Proficiency score; S are the years of school and *e* a residue, coefficient b reflects both the selection and the real effects of school.

To separate selection from effects, experimental designs should be used. Given their difficulty, it may be wise to search for real situations where both are separate, enabling natural experiments or quasi-experiments. In any case, two competency assessments are necessary, one before and another one after the factor, selection or schooling, that the real situation allows to estimate. . In the case of the school effect, we have:

$$PLP_{it+1} = PLP_{it} + bS_i + e, \ (2)$$

[2] The IALS study provided correlations ranging in the European countries from 0.58 in Ireland to 0.47 in Holland. In Chile it is higher, 0.68. Cf. Desjardins, 2003.

where the subscripts t refer to time.

Although PIAAC is a synchronic study which only measures competencies once, its data offer possibilities of attributing values to PLP before and after both types of “treatment”, selection and schooling.

The first possibility is based on the consideration of groups or categories whose differences in years of school do not have PLP as its origin, but only as its consequence (unlike what happens with individuals). That is,

$$PLP_m = a + bS_m \text{ , (3)}$$

where the subscript m indicates the median of groups whose schooling does not depend on their abilities. In this strategy, the PLP of the group or category with less schooling is taken as plp ‘ante’. As we shall see later, more useful here than gender or territory, is the birth cohort. The date of birth is random. If a generation goes to school more than the previous one, or than the next one, it is far more likely that this is due to any type of exogenous causes than to differences in PLP developed by each generation before going to school.

The intercohort variations in PLP associated to the years of school can in fact be due to other causes, for example, the quality of the school. The objective of reforms is usually quantity as well as quality. Through intercohort variations it is possible to estimate the effect of the years of school in general, without distinguishing levels. A comparison by levels of education will also help distinguish the specific effect of years of school wihin each level.

The second possibility is based on the fact that after compulsory education students choose different academic tracks. This suggests attributing to selection the differences in PLP at the start of each level. Although it only gives us a score, PIAAC allows two ways of controlling PLP before starting each level. One is to estimate (1) for each level. The constant *a* would indicate the start PLP and coefficient *b* the effect of every year of school. An evident bias of this approach is that it takes as the entry level that of those first dropping out, which is probably an underestimation. Also, within each level the selection is still being confused with the real effects. A possible correction of these biases would come from assuming that students who finish their education started with higher PLP than those who dropped out, and thus estimating the effect of the years of schooling after controlling for this variable. That is, for each level,

$$PLP_{in} = a + b_1S_n + b_2F_n + e, \text{ (4)}$$

which resulsy from replacing in (2) PLP_t with a, and where F means finishing the level.

A better approach is to take as the PLP “ante” value the one of the generations that are starting each level at the time of the PIAAC study. Indeed, among those starting post-compulsory schooling, PIAAC measures initial PLP, not the final one. At the moment PIACC was carried out, respondents aged 16 and 17 were finishing compulsory education, after which they leave school or start several types of post-compulsory education. Their PIAAC scores are good estimates of the PLP of those just entering each level, and therefore of the selection effect. The school effects can be estimated by comparing the PLP of those continuing in school with those who have dropped out. To the extent that additional years of school determine PLP, student scores should rise more than those of non-students. It is true that growth does not reflect an unconditional effect of school, but rather conditioned by student PLP. We cannot ascertain that the effects of a lower PLP would have been the same had the dropouts continued in school. What is being estimated, therefore, is the upper or maximum limit of the years of school.

The difference between those continuing and those not is the overall selection effect. We can separate the students who continue depending on the type of education they chose at each divide, attributing to the years of schooling the differences with the just stating cohort. The difficulty of this procedure is that, as PIAAC is not a longitudinal study, we have to assume zero effects of the cohort and the period at the age in which school is left; specifically, we must assume that the PLP scores and the student distribution were the same for the various generations at age 16. Fortunately, the PISA studies and education statistics almost assure this has been so in the last ten years, that is, among respondents aged 18 to 27.

Variables

We transformed some variables in order to adapt them to these methods.

We grouped the date of birth in five-year cohorts numbered since the start of the 20th century. The first cohort interviewed for the PIAAC study is number 10 (1946-50) and the last one number 19 (1991-95). This grouping in five-year cohorts maintains almost all the effects of age and allows treating homogeneous groups in terms of the academic system of their schooling (cohorts 10 and 11 before the Laws of 1964 and 1965 that extended schooling from age 12 to 14; cohorts 13 to 16 with the General Law of Education of 1970; cohort 17 in the transition between the General Law of Education and the LOGSE *[General Organic Law of the Educational System]* of 1991, and cohorts 18 and 19 completely with the LOGSE).

The level of education started and completed is very important for our purpose. PIAAC reports the highest level of education attained and started. Education levels are pre-coded in eleven categories. The coding had several failings. One is the usual one of not distinguishing between education from different times thet were officially declared as equivalent, which deletes from history the former *Bachillerato Elemental*. Onother r one is not to distinguish between those who completed Basic Education as Graduates and those who did not. Another one is that Vocational Education, which follows Elementary or Primary Education (successively termed *Oficialía Industrial, PFI* and *CFGM*), is put together with *Bachillerato [Upper Secondary Education]* (however, the former 5-year Degrees have not been confused with the current Bachelor Degrees from the Bologna process)[3]. Following a detailed study of the information provided by PIAAC we have built two main variables, ESTUF (highest educational level completed) and ESTUE, (highest educational level started).

[3] It seems this is partly due to certain confusion between identification of studies and their classification in the ISCED categories, which in turn originates from not following the rule of unique species coding.

Years of schooling are the crucial variable. Unfortunately, the information provided by PIAAC only allows building it with many problems. PIAAC attributes years to completed education (*yrsqual*), but evidently this is not a good estimate of actual years of school. IT also asks about the age when leaving highest education completed, but not the age when starting. Subtracting 6 from that age gives a good estimate of the years of schooling of the younger cohorts, but since as age increases there are more people leaving school at older ages, accuracy is lost for older cohorts. We have tried to overcome this issue by placing a limit on the years of school for each education level and leaving out of certain estimates those exceeding that limit (late education). The result is the ESCUELE variable.

The dependent variable will always be the first valid value of Literacy. We have referred to it as PLP, acronym for PIAAC Literacy Proficiency.

Tables 2.1 and 2.2 show the evolution of education started and completed by five-year birth cohorts. Table 2.3 the evolution of years of school and PLP.

Table 2.1. Educational level attained by five-year birth cohort

COHORT	EDUCATIONAL LEVEL COMPLETED									Total
	PRE-SCHOOL	PRIMARY	EGB	FPI	BUP	FPII	DIPLOMA	BA DEGREE	DOCTORATE	
10-46A50	13.9%	39.9%	18.0%	1.7%	13.0%	3.4%	5.5%	4.1%	.5%	100.0%
11-51A55	10.3%	27.8%	26.0%	1.2%	14.2%	4.3%	9.3%	6.5%	.4%	100.0%
12-56A60	5.1%	20.7%	28.9%	1.8%	17.6%	7.1%	10.0%	7.4%	1.5%	100.0%
13-61A65	3.5%	20.9%	26.6%	2.1%	16.3%	8.2%	7.8%	13.8%	.7%	100.0%
14-66A70	2.0%	15.6%	28.3%	3.4%	14.1%	11.9%	11.4%	13.0%	.3%	100.0%
15-71A75	1.5%	15.9%	20.6%	2.3%	14.6%	14.1%	13.1%	17.0%	1.0%	100.0%
16-76A80	1.1%	10.6%	21.5%	3.0%	16.0%	13.9%	14.1%	19.0%	.8%	100.0%
17-81A85	1.4%	8.4%	27.4%	2.9%	18.8%	10.7%	15.6%	14.5%	.2%	100.0%
18-86A90	.9%	9.0%	28.4%	2.8%	31.9%	6.8%	12.3%	7.7%	.2%	100.0%
TOTAL	4.2%	18.4%	25.2%	2.4%	17.2%	9.2%	11.1%	11.8%	.6%	100.0%

Table 2.2. Educational level started by five-year birth cohort

COHORT	EDUCATION LEVEL STARTED									Total
	PRE-SCHOOL	PRIMARY	EGB	FPI	BUP	FPII	DIPLOMA	BA DEGREE	DOCTORATE	
C10/46-50	12.5%	38.5%	18.3%	1.9%	11.1%	3.6%	8.2%	5.0%	1.0%	100.0%
C11/51-55	9.5%	26.0%	24.7%	1.2%	12.2%	6.1%	9.7%	10.1%	.4%	100.0%
C12/56-60	4.4%	19.4%	24.7%	1.8%	18.7%	7.1%	11.1%	11.1%	1.8%	100.0%
C13/61-65	3.2%	16.5%	21.1%	2.5%	20.7%	9.8%	8.7%	16.7%	.9%	100.0%
C14/66-70	1.6%	11.9%	22.0%	3.1%	17.2%	14.1%	13.3%	15.8%	1.0%	100.0%
C15/71-75	1.0%	11.6%	15.9%	2.3%	18.3%	14.1%	15.1%	20.1%	1.6%	100.0%
C16/76-80	1.0%	7.0%	17.1%	2.5%	18.1%	14.8%	14.1%	23.6%	1.9%	100.0%
C17/81-85	.9%	2.9%	23.4%	3.4%	20.2%	11.1%	15.0%	21.3%	1.8%	100.0%
C18/86-90	.4%	2.8%	20.4%	3.3%	20.6%	11.8%	20.1%	19.9%	.7%	100.0%
C19/91-95		1.0%	26.5%	1.0%	42.0%	8.8%	17.9%	2.9%		100.0%
TOTAL	3.3%	13.6%	21.3%	2.3%	19.9%	10.4%	13.3%	14.9%	1.1%	100.0%

Table 2.3, Descriptive statistics, ESCUELE and PIAAC literacy

COHNA5		ESCUELE	PIACC LITERACY
C10/46-50	Average	9.24	218.76
	N	414	416
	Stand, Dev,	4.52	49.92
C11/51-55	Average	10.37	228.57
	N	491	493
	Stand, Dev,	4.88	48.49
C12/56-60	Average	11.57	241.16
	N	552	553
	Stand, Dev,	4.63	48.93
C13/61-65	Average	12.12	252.71
	N	563	565
	Stand, Dev,	4.88	47.66
C14/66-70	Average	12.71	257.87
	N	615	615
	Stand, Dev,	4.45	46.20
C15/71-75	Average	13.70	266.80
	N	609	611
	Stand, Dev,	4.65	45.66
C16/76-80	Average	14.37	268.19
	N	525	526
	Stand, Dev,	4.34	42.24
C17/81-85	Average	14.40	267.29
	N	441	441
	Stand, Dev,	4.06	42.15
C18/86-90	Average	13.86	266.97
	N	457	458
	Stand, Dev,	2.98	46.16
C19/91-95	Average	11.53	260.02
	N	491	491
	Stand, Dev,	1.71	40.70
Total	Average	12.44	253.50
	N	5158	5169
	Stand, Dev,	4.53	48.57

Source: PIACC data

RESULTS

Table 2.4 shows the result of estimating the influence of school on PLP without separating between real and selection effects. Not controlling other variables, the highest level completed (transformed into years, variable "yrsqual" of the database) appears associated to 7.6 additional points on the PIAAC literacy scale, approximately 0.16 SD, with 0.56 being the correlation between the two variables. Although the correlation is the same, the coefficient of actual years (variable ESCUELE) is quite lower, close to 6 points, 0.12 SD. Both variables together mutually halve their coefficients without increasing by more than 2 points the goodness of fit (take into account that the correlation between them is 0.86). Even being completely gross, these estimates are already lower than many found in literature. The correlation of 0.56, however, is in the high range of those found in the European countries participating in the IALS (Desjardins, 2012).

Table 2.4. Influence of school on PIAAC literacy, with no controls

A, YEARS OF SCHOOLING CALCULATED FOR THE HIGHEST LEVEL ATTAINED						
Model		Non-standardised coefficients		Standardised coefficients	t	Sig,
		B	Standard error	Beta		
1	(Constant)	168.214	1.838		91.533	0.000
	SCHOOL ATTRIBUTED	7.605	.156	.561	48.743	0.000
a, Independent variable: PIACC LITERACY						

B, YEARS OF SCHOOLING CALCULATED FOR THE HIGHEST LEVEL STARTED						
Model		Non-standardised coefficients		Standardised coefficients	t	Sig,
		B	Standard error	Beta		
1	(Constant)	179.415	1.636		109.699	0.000
	ESCUELE	5.961	.124	.558	48.259	0.000
a, Independent variable: PIACC LITERACY						

Source: PIACC data

Secular changes

Age is not the only variable to form groups whose inequalities in PLP depend only on their years of school. We can also consider gender. Males and females are subject to the same schooling conditions, and, although there are differences in the rate of acquisition of competencies, they are not large and at times favour males (*numeracy*) and at times females (*literacy*). But this variable is not useful because gender differences in schooling ceased to exist more or less in cohort 10, right when the PIAAC sample begins.

Territory also seems a good candidate. But neither are there enough differences in schooling by territory. Dividing Spain into north (Aragón, Asturias, Cantabria, Castilla-León, Catalonia, Galicia, Madrid, Navarra, Rioja and Basque Country) and south (Andalucía, Balearic Islands, Canary Islands, Castilla La Mancha, Extremadura, Murcia, Valencia, Ceuta and Melilla), it turns out that the north exceeds the south slightly in length of schooling and in PLP in the older cohorts; but from cohort 16 to the present these differences disappear, unlike what happened in PISA (Carabaña, 2008). Overall, the variable is so insignificant I have preferred to leave it out.

Grouping by five-year birth cohorts ("cohna5") has initially more problems than gender and region, for as well as to years of school, the differences in PLP could be due to the effects of age (positive in younger ages, negative in adults) and the characteristics of the cohort (such as size, educational reforms, or the economic situation). But it is more useful because it provides greater variation in years of school.

The increase in schooling in the second half of the 20th century leads us to predict an increase in PLP that allows estimating the influence of one over the other. Table 2.3 reflects an almost perfectly parallel evolution until cohort 16: five years more of schooling, 50 points more of PLP. We could put forward that until then a year of school increased PLP by 10 points (depending on the cohort, between 0.25 and 0.20 SD, in the high range of the preceding ones). In cohort 16, however, schooling increases 0.7 years with hardly any variation in the PLP score. After cohort 17, schooling diminishes, but PLP does not. Cohort 19, with three years less of schooling than 17, has only 7 PLP points less (2 points per year, 0.04 SD, the lowest of the range observed by others).

We have said that the fall of PLP in the older cohorts may rely on factors other than school. Ageing reduces it, more or less with varying estimates (Desjardins and Warnke, 2012)[4]. In many countries (perhaps also in Spain, according to Colom et al, 1998) sharp rises in IQ have been detected in the post-war generations (Flynn, 1987). The effects of years of school can be separated from the remaining factors keeping years of schooling constant. Table 2.5 shows that between cohorts 10 and 15, Spaniards at all intervals of schooling increased their PLP by approximately 25 points. The other 25 are those left for the 5-year increase of schooling, around 5 points per year, approximately 10-12% SD. The 25 points common to all years of school could be due to age decreases, increases due to the Flynn effect, rises in school quality or other factors.

Strictly speaking, the averages in each cohort depend on three factors: the common increases abovementioned, the years of school and the PLP value of each year of school. Regression in Table 2.6 shows the general increases as constant and the value of each year of school as coefficient. The constant grows a total of 23 points to cohort 16, instead of the 25 estimated in Table 2.5, so there are 27 remaining for the five years of school that distinguish cohort 16 from 10, to somewhat over 5 points of PLP per year. Coefficients are between 5 and 5.5 points, with a few lower exceptions. In cohort 16, the drop compensates the half-year increase of school, and explains the small enigma of why the average did not grow in that cohort.

[4] For IQ, the most reliable indicate an age of decline much later than the 40 of cohort 15 (Schaie, 2013).

Table 2.5. PIAAC Literacy by Birth Cohorts and Schooling Intervals

COHNA5		LESS THAN 6	6 TO 8	8 TO 10	10 TO 13	13 TO 16	16 OR MORE	TOTAL
C10/46-50	AVERAGE	188.4	214.8	212.4	248.4	238.5	266.6	218.9
	STAND. DEV.	48.6	44.5	41.4	39.6	42.8	41.3	50.0
	CASES	100	130	59	53	37	35	414
C11/51-55	AVERAGE	200.8	212.7	226.6	247.2	242.3	269.3	228.4
	STAND. DEV.	46.6	44.9	44.0	35.4	42.8	39.0	48.4
	CASES	93	137	67	63	63	68	491
C12/56-60	AVERAGE	193.2	220.3	230.8	253.1	257.9	277.3	241.4
	STAND. DEV.	52.2	44.7	41.7	40.5	36.7	39.3	48.7
	CASES	45	143	82	106	79	97	552
C13/61-65	AVERAGE	191.6	228.4	242.2	263.3	258.9	291.9	253.0
	STAND. DEV.	46.9	39.9	36.9	34.8	42.1	36.3	47.4
	CASES	39	119	102	104	73	126	563
C14/66-70	AVERAGE	185.5	237.2	235.5	260.9	268.3	291.0	257.9
	STAND. DEV.	44.7	40.0	40.9	39.0	33.4	37.1	46.2
	CASES	24	102	116	127	92	154	615
C15/71-75	AVERAGE	212.2	238.0	241.4	262.9	269.6	295.2	266.7
	STAND. DEV.	36.2	37.5	39.9	40.9	38.4	38.5	45.7
	CASES	22	71	101	99	110	206	609
C16/76-80	AVERAGE	203.4	238.2	238.7	260.9	271.3	291.8	268.1
	STAND. DEV.	42.5	37.4	38.6	33.8	38.4	34.2	42.2
	CASES	7	37	91	82	121	187	525
C17/81-85	AVERAGE	198.6	241.3	240.8	253.1	269.6	292.8	267.3
	STAND. DEV.	62.8	33.0	35.1	35.7	40.9	31.8	42.1
	CASES	8	26	55	91	116	145	441
C18/86-90	AVERAGE	197.9	213.1	241.3	244.7	280.0	297.7	267.4
	STAND. DEV.	58.7	40.6	41.8	39.8	37.9	36.7	45.5
	CASES	8	14	43	102	229	61	457
C19/91-95	AVERAGE	199.3	215.4	252.0	263.5	273.7		260.0
	STAND. DEV.	73.9	46.0	36.7	40.6	33.0		40.7
	CASES	3	18	122	274	74	0	491
TOTAL	AVERAGE	194.8	224.3	237.6	257.7	267.8	289.3	253.6
	STAND. DEV.	48.0	43.1	40.5	39.1	39.8	37.4	48.5
	CASES	349	797	838	1101	994	1079	5158

Source: PIACC data

DIF PLP COHORT 12-10	4.9	5.5	18.4	4.7	19.4	10.7	22.5
DIF PLP COHORT 15-12	19.0	17.7	10.6	9.9	11.7	17.8	25.4
DIF PLP COHORT 17-15	-13.6	3.2	-0.6	-9.9	0.0	-2.3	0.6
DIF AVERAGES PLP BETWEEN INTERVALS		29	13	20	10	21	

Furthermore, it is remarkable that the correlation –appearing in Table 2.6 as a beta coefficient– between years of school and PLP increases from 0.47 in cohort 10 to 0.56 in cohort 13, and from then on, it is steady. This increase should be related to the decrease in the standard deviation of the PLP, which goes from 50 to 45, and with slight fluctuations in SD of the years of school around 4.5.

Therefore, the PLP averages grow first with the passing of time and then they level off. Growth depends equally on the secular trend of unidentified causes – age, Flynn effect, school quality, other – and the rise in the years of schooling. Since these grow about five years and they can be attributed 25 points of the improvement in PLP, the result is an estimate of 5 points per year. This estimate based on variation between cohorts coincides with that estimated inside each cohort. Accordingly, the simple initial model would barely be biased and PLP would depend entirely on the years of school at a rate of 5 points, slightly more than 0.10 SD per year, at least in cohorts 10 to 15.

After cohort 15, growth stops, as do the three components it relies on:

- Whatever the cause, the secular trend disappears.
- Somewhat unexpectedly (don't the young today spend more years in school than those twenty years ago?) the years of school also stopped growing, although those of cohort 17 could still increase, as they are between 26 to 30 years old.
- The school coefficient within cohorts is maintained around 5 points.

It seems we must accept as valid the 5 PIAAC points for every year of school. This is slightly more than 10% SD, a low estimate, the minimum estimate in literature.

However, in Tables 2.3, 2.5 and 2.6 there are indications that promise different coefficients for the years of post-compulsory education. First, in Table 2.5 not all years of school are associated to the same increases in PLP. The years between 8 and 10 and between 13 and 16 are not very productive, and furthermore, there are differences between the old and the young cohorts. Data have been analysed in detail, and no satisfactory manner of separately estimating the effect of the years of elementary education has been found. The major difference, 29 points, between those with less than 6 years of school and those with 6 to 8 is not very informative, not only because of the possibility of reverse causality –among the older cohorts the low achievers left primary education earlier-, but because the years of education of those not completing primary education have not been observed, but rather attributed (PIAAC does not ask those not attaining at least a Primary "certificate" when they left school)[5].

Second, the school coefficient in cohorts 18 and 19 is much higher than in the others (8.4 and 6.8 points, respectively); given their age, many have not yet completed their education, but their average PLP is already almost the same as that of previous generations, which could well mean that their PLP is already developed and the additional years of school have little influence on it[6].

[5] Villar found different results (2013), in this same publication.

[6] As age and schooling increase in future the PLP of these cohorts, their actual years of school shall be more efficient than those of previous generations.

Table 2.6. Influence of Years of School on PIAAC Literacy, by Cohorts

COHNA5		Non-standardised coefficients		Standardised coefficients	t	Sig.
		B	Standard error	Beta		
C10/46-50	(Constant)	170.485	4.942		34.496	.000
	ESCUELE	5.237	.481	.473	10.896	.000
C11/51-55	(Constant)	179.307	4.518		39.684	.000
	ESCUELE	4.738	.394	.477	12.010	.000
C12/56-60	(Constant)	179.234	4.809		37.269	.000
	ESCUELE	5.368	.386	.510	13.913	.000
C13/61-65	(Constant)	187.046	4.430		42.222	.000
	ESCUELE	5.440	.339	.561	16.040	.000
C14/66-70	(Constant)	185.911	4.730		39.304	.000
	ESCUELE	5.664	.351	.546	16.118	.000
C15/71-75	(Constant)	192.274	4.800		40.060	.000
	ESCUELE	5.436	.332	.554	16.383	.000
C16/76-80	(Constant)	193.837	5.404		35.871	.000
	ESCUELE	5.167	.360	.532	14.351	.000
C17/81-85	(Constant)	187.474	6.263		29.932	.000
	ESCUELE	5.542	.419	.534	13.240	.000
C18/86-90	(Constant)	151.012	8.472		17.824	.000
	ESCUELE	8.396	.598	.550	14.045	.000
C19/91-95	(Constant)	180.970	12.028		15.045	.000
	ESCUELE	6.855	1.032	.288	6.643	.000

a, Independent variable: PIACC LITERACY

Source: PIACC data

Reforms

If as a result of an exogenous cause that left everything else the same, discontinuities were reported in the years of school between the generations, parallel variations would be expected on the PLP. This is the strategy followed by Brinch and Galloway with data for the whole of Norway (2012). In Spain, there have been legal stipulations to increase both the years of compulsory education and those necessary to attain certain certificates, so we could try to trace their influence.

Law 27/1964, of 29 April, (BOE 4-5-64) extended compulsory education from 12 to 14 for Spaniards born in or after 1954 (final stipulation). Law 169/1965 of 21st December, on the reform of Primary Education (BOE *[Official Gazette]* 306, 23-12-65) specified it was an 8-year elementary education, from age six to 14, which had to be studied until the age of ten in primary schools, and between ten and 14 in those same schools or in the various types of middle schools (Art. 12). Most of these centres were Institutes of *Bachillerato* or Secondary Education, whose entrance examination was abolished by that same Law.

The General Law of Education (LGE) of 1970 established elementary education until the age of 14, and a decree implementing it extended compulsory education to the age of 16. The LGE in its Article 2.2 stated that “General Elementary Education shall be compulsory and free for all Spaniards. Those not continuing in education, shall receive, also compulsorily and for free, first level vocational education (FPI)”. It also stated that this compulsory FPI would have “the necessary duration to become proficient in the corresponding speciality, without exceeding two years per qualification”. This maximum duration was chosen as the only one by Decree 707/1976 (art. 3.2). In 1990, the LOGSE did not increase compulsory education to age 16, but only expanded basic education to that age, deleting the difference between BUP and FPI. However, it did something certainly more efficient to increase the years of school: it increased from eight to ten the number of years necessary to obtain a Graduate Certificate and, also, it turned it into the key necessary to pursue any type of further education. Students who under the LGE left EGB to pursue FP, were forced under the LOGSE to obtain an ESO “qualification” if they wanted to continue studying.

As for post-compulsory education, the BUP established by the LGE lasted a year more than its predecessor *Bachillerato Superior*, which increased by one year the duration of the whole. The greater increase of all, four years, affected the former Middle Degrees. The abovementioned Law of 1964 required *Bachillerato Superior* to be able to access Teacher Training, and shortly afterwards, the LGE turned all these Middle Degrees (Teacher Training, Technical Studies, Nursing) into three-year university diplomas. Therefore, a student born in 1953 could still obtain one of these TGM *[middle Degrees]* at the age of 17, after 11 years of school (four in Primary, four of Lower Secondary and three in a Middle School), but after the LGE, students born after 1960 needed 15 (eight of EGB, four of BUP and three in university).

In the PIAAC data, the impact of these stipulations on the years of school can be detected better in some cases than in others (Table 2.7). Extending compulsory education to the age of 14 years is reflected in cohort 12 increasing the years of elementary education by 0.8. We can also attribute to the shift from Middle Degrees to Diplomas the approximately 1.5 more years of schooling in UNI1 between cohorts 10 and 12. In contrast, in the following cohorts there is no noticeable influence of LGE[7], either on total schooling, which increases less than in the previous cohorts, or on any other level. As for the LOGSE, there is no increase in years for those starting CFGS, and of the one and a half years more (from 8.7 in cohort 15 to 10.3 in 19) spent in basic education by students who study no further, only the 0.4 points between cohorts 17 and 19 can be attributed to it. In order to be thorough, it should be noted that between cohorts 14 and 17, without coinciding with any reform, there is an increase of 1 point in the years of school for *Bachillerato*, FPII and 3-year university Diplomas (UNI1).

[7] It is well known, although little believed, that by requiring more years for the same qualifications, the LGE broke the growing trend of starting Bachillerato and University, especially among males (Carabaña, 1997; 2012), but it was assumed that, for the same reason, the years of schooling had increased. This information is unknown, as far as we know.

Table 2.7. Years of school by Birth Cohort and Education Level Started

YEARS OF SCHOOLING		EDUCATION LEVEL STARTED					TOTAL
		ELEMENTARY	FP-BACH	FPII	UNI1	UNI2	
C10/46-50	AVERAGE	7.0	11.4	14.1	15.1	18.7	9.2
	CASES	286	52	17	34	25	414
	STAND, DEV,	2.7	2.5	2.7	2.7	3.1	4.5
C11/51-55	AVERAGE	7.4	11.7	12.6	16.0	18.7	10.4
	CASES	292	67	33	47	52	491
	STAND, DEV,	2.8	2.8	3.1	2.5	2.8	4.9
C12/56-60	AVERAGE	8.2	11.8	13.2	16.9	18.4	11.6
	CASES	265	111	43	61	71	551
	STAND, DEV,	2.6	2.4	2.8	2.3	2.9	4.6
C13/61-65	AVERAGE	8.1	11.3	13.6	16.3	19.0	12.1
	CASES	223	132	59	49	99	562
	STAND, DEV,	2.4	2.2	2.7	2.4	2.3	4.7
C14/66-70	AVERAGE	8.7	11.4	13.2	16.5	18.9	12.7
	CASES	211	126	93	82	103	615
	STAND, DEV,	2.4	2.4	2.6	2.3	2.1	4.5
C15/71-75	AVERAGE	8.7	11.7	14.7	16.8	19.2	13.7
	CASES	170	127	88	91	133	609
	STAND, DEV,	2.4	2.6	2.6	2.1	2.0	4.7
C16/76-80	AVERAGE	9.5	12.3	14.4	17.3	19.1	14.4
	CASES	128	107	82	74	134	525
	STAND, DEV,	2.3	2.4	2.6	1.9	2.1	4.3
C17/81-85	AVERAGE	9.9	13.0	14.9	17.4	18.6	14.4
	CASES	115	100	58	66	102	441
	STAND, DEV,	2.5	2.3	2.5	1.8	2.3	4.1
C18/86-90	AVERAGE	10.2	12.8	15.0	15.7	16.5	13.9
	CASES	103	103	65	92	94	457
	STAND, DEV,	2.4	1.9	1.5	1.7	1.3	3.0
C19/91-95	AVERAGE	10.3	11.1	13.0	12.9	12.9	11.5
	CASES	117	206	66	88	14	491
	STAND, DEV,	1.9	1.2	1.1	.8	1.0	1.7
TOTAL	AVERAGE	8.4	11.8	13.9	16.1	18.5	12.4
	CASES	1910	1131	604	684	827	5156
	STAND, DEV,	2.7	2.3	2.5	2.4	2.5	4.5

Source: PIACC data

Table 2.8, PIAAC Literacy by Birth Cohort and Level of Education Started

		EDUCATION LEVEL STARTED					TOTAL
		ELEMENTARY	FP-BACH	FPII	UNI1	UNI2	
C10/46-50	AVERAGE	203.7	241.9	245.0	260.3	270.1	218.8
	CASES	288	52	17	34	25	416
	STAND, DEV,	46.9	34.7	44.0	36.2	39.4	49.9
C11/51-55	AVERAGE	212.0	236.3	240.3	261.3	274.6	228.6
	CASES	293	67	33	48	52	493
	STAND, DEV,	45.7	39.8	36.1	42.2	35.9	48.5
C12/56-60	AVERAGE	217.5	248.1	255.7	269.6	286.0	241.3
	CASES	265	111	43	61	71	551
	STAND, DEV,	46.9	38.5	27.8	36.7	36.6	48.7
C13/61-65	AVERAGE	225.3	254.0	257.7	279.8	295.8	252.6
	CASES	224	132	60	49	99	564
	STAND, DEV,	45.9	35.4	32.8	36.3	35.3	47.6
C14/66-70	AVERAGE	229.4	254.6	264.4	281.0	296.0	257.9
	CASES	211	126	93	82	103	615
	STAND, DEV,	43.2	39.9	35.0	39.4	33.1	46.2
C15/71-75	AVERAGE	235.1	255.1	270.1	280.2	307.3	266.8
	CASES	171	127	88	92	133	611
	STAND, DEV,	40.8	37.9	35.8	35.4	34.5	45.7
C16/76-80	AVERAGE	233.0	262.6	270.3	279.4	298.8	268.2
	CASES	128	108	82	74	134	526
	STAND, DEV,	40.0	34.0	35.2	32.2	32.1	42.2
C17/81-85	AVERAGE	239.8	255.3	274.0	285.8	294.3	267.3
	CASES	115	100	58	66	102	441
	STAND, DEV,	40.4	38.1	37.0	32.2	32.4	42.1
C18/86-90	AVERAGE	224.0	259.2	269.8	289.1	300.8	267.4
	CASES	103	103	65	92	94	457
	STAND, DEV,	41.6	38.1	31.6	31.2	35.3	45.5
C19/91-95	AVERAGE	229.9	260.4	269.1	287.2	292.1	260.0
	CASES	117	206	66	88	14	491
	STAND, DEV,	43.3	34.0	33.3	31.5	25.9	40.7
TOTAL	AVERAGE	221.9	254.6	264.9	279.6	295.5	253.5
	CASES	1915	1132	605	686	827	5165
	STAND, DEV,	45.6	37.3	35.3	35.8	35.2	48.5

Source: PIACC data

Table 2.8 allows analysing both the general effect and the particular effects of these reforms. A general effect cannot be denied, although not asserted either. In fact, the increase in PLP in cohorts 12 and 13, coinciding with the reforms of 1964-65 and with the LGE, is 3 points higher than in cohort 11 and than in cohort 14. This is a difference which, statistically, has as many probabilities of occurring among the population as not[8]. As for the particular effects, it is easy to see that:

- the increase of Primary of 0.8 points in cohort 12 is not associated to a particular increase in PLP;
- the increase of 1.5 years in TGM/diplomas between cohorts 11 to 13 does not correspond to any particular increase of PLP,
- the increase of 0.4 points in ESO between cohorts 17 to 19 is associated to a decrease of 6 to 10 points (depending on whether we consider the peak score of cohort 17, verging on statistical significance). This is especially interesting as it corresponds to the rise of schooling at the end of elementary education (EGB and ESO) occurring in the last two decades in line with the fight against the so-called "academic failure"; and
- the increase of one year in *Bachillerato*, FPII and 3-year university Diplomas, which we cannot quite associate to any particular cause, only in FPII could it be linked to an increase of 6 points in the PLP, barely significant in statistical terms.

In summary, the attempt to examine the effects of the reforms has not reached any decisive conclusion on their general effects. However, it has led us to examine the increases in the years of school in particular levels of education. The most accurate thing that can be said is that perhaps one of them has had positive effects and another one negative ones on PLP. A very different result from the 5 points per year obtained with the previous procedures, which encourages us to continue our research.

Selection and Causality in Post-Compulsory Education

So far the first strategy has been used to identify the effects of school, based on variations between cohorts. Now we shall look at the results of using the second one, based on the differences in schooling inside each level of education. We can assume that those starting a level of education do so for more or fewer years regardless of their initial PLP, and therefore the equation (1) is a good model of the influence of the years of school; however, it seems better to estimate the equation (4), that tries to control selection inside the levels of education and attributes to it the differences between those who complete the level and those who do not. To avoid other uncontrolled effects, the estimate has been limited to cohorts 15, 16 and 17, who studied mostly under the LGE and have similar average scores; also, we have left out those who completed their education late.

[8] With a SD of nearly 50, statistical significance of 5% needs to either double the difference or quadruple the sample. In this same publication, Robles (2013) found a general effect of implementation of the LOGSE, from 1978 to 1983.

Table 2.9. Years of Schooling and PIAAC Literacy by Educational Level Started. Cohorts 15 to 17

A. DESCRIPTIVE STATISTICS				
EDUCATION LEVEL STARTED		Average	Standard deviation	N
ELEMENTARY	PIACC LITERACY	242.018	37.089	252
	ESCUELE	9.714	1.842	252
	COMPLETED	0.825	0.380	252
FP-BACH	PIACC LITERACY	256.478	36.328	282
	ESCUELE	12.099	2.150	282
	COMPLETED	0.589	0.493	282
FPII	PIACC LITERACY	274.489	34.073	184
	ESCUELE	14.614	2.021	184
	COMPLETED	0.793	0.406	184
UNI1	PIACC LITERACY	278.436	33.493	175
	ESCUELE	16.817	1.752	175
	COMPLETED	0.766	0.425	175
UNI2	PIACC LITERACY	297.444	31.931	265
	ESCUELE	18.543	2.020	265
	COMPLETED	0.751	0.433	265

B. REGRESSION COEFFICIENTS							
EDUCATION LEVEL STARTED			Non-standardised coefficients		Standardised coefficients	t	Sig.
			B	Standard error	Beta		
ELEMENTARY	1	(Constant)	224.900	12.544		17.929	.000
		ESCUELE	1.762	1.269	.088	1.389	.166
	2	(Constant)	218.580	12.559		17.404	.000
		ESCUELE	.890	1.287	.044	.692	.490
		COMPLETED	17.917	6.231	.184	2.875	.004
FP-BACH	1	(Constant)	252.428	12.404		20.350	.000
		ESCUELE	.335	1.009	.020	.332	.740
	2	(Constant)	256.354	12.911		19.856	.000
		ESCUELE	-.255	1.144	-.015	-.223	.824
		COMPLETED	5.453	4.992	.074	1.092	.276
FPII	1	(Constant)	251.348	18.353		13.695	.000
		ESCUELE	1.583	1.244	.094	1.273	.205
	2	(Constant)	251.498	18.424		13.650	.000
		ESCUELE	1.631	1.279	.097	1.275	.204
		COMPLETED	-1.058	6.370	-.013	-.166	.868
UNI1	1	(Constant)	224.730	24.228		9.276	.000
		ESCUELE	3.194	1.433	.167	2.229	.027
	2	(Constant)	227.645	25.316		8.992	.000
		ESCUELE	2.897	1.610	.152	1.799	.074
		COMPLETED	2.709	6.641	.034	.408	.684
UNI2	1	(Constant)	248.275	17.919		13.855	.000
		ESCUELE	2.652	.961	.168	2.760	.006
	2	(Constant)	251.615	18.520		13.586	.000
		ESCUELE	2.326	1.061	.147	2.192	.029
		COMPLETED	3.580	4.950	.049	.723	.470

a, Independent variable: PIACC LITERACY
Source: PIACC data

Table 2.9A shows the descriptive statistics and Table 2.9B the results of estimating the equation (4). The coefficients range between 0.335 points of PLP per year of school for BUP and 3.19 points for 3-year university diplomas. Completing education, which is introduced in model 2, is important in itself (around 18 points) and because it modifies the coefficient of the years of school (from 1.76 to 0.89) only at the EGB level. In the higher levels, the years of school are more important and having completed education or not is not very relevant.

This estimate is much lower than the previous one of 5 points. It seems strange, however, that the years of university are more important than those of intermediate education. To assess these results we should take into account the averages and SD of Table 2.9A. Thus, in spite of having left out those finishing late (not many yet at this age), undergraduate students have left education on average after 18.5 years of school, with a SD of 2.2; nearly half of the undergraduate students continue studying after the age of 25, and over 30% after 27. However, those years continue having a positive effect on PLP, whether education is completed or not.

The assumption of independence between PLP and years of school could have a problem, especially on the final levels. To the extent that students with the lowest PLP dropout earlier, there is a positive association between PLP and continuing education. To the extent that students with an initially lower PLP repeat years and are delayed more, the correlation between PLP and years of school is negative. Indeed, certain very selective careers are also longer or more difficult, but also part-time students, who take longer to complete their studies, choose easier careers. I have tried unsuccessfully to take all this into account to explain the strange effect on PLP of delaying education.

The PIAAC data help getting around the weakness of the previous procedure when they provide the PLP observed before starting a level of education, which happens only for the youngest cohort. This allows estimating (2) with the “ante” PLP observed, in exchange for taking the S of the variation between birth cohorts. That is, being so far cross-sectional study, PIAAC normally provides the PLP after completing education. However, respondents aged 16 and 17 are examined just when they are starting CFGM *[Intermediate VET]* and *Bachillerato*. We know, therefore, how the older ones finish and the younger ones start. If we could assume that the older ones started at the time as the young ones now, we could attribute to years of school the difference in PLP that PIAAC finds between them.

In reality, we know for a fact that essentially cohorts 18 and 17 began the same as 19. We know, first of all, that their scores in tests very similar to PIAAC were the same. The PIAAC 18-year-olds are those of PISA 2009, the PIAAC 21-year-olds are those of PISA 2006, and those 24 and 27 years old when PIACC are the same people examined by the two previous editions of PISA, 2003 and 2000. Also, tests conducted earlier by the MECD lead to the conclusion that the introduction of the LOGSE did not change student learning either, allowing us to extend the assumption of a similar start at least for cohort 17 (Carabaña, 2009).

We also know that students in cohorts 16 to 18 are distributed when finishing EGB and ESO similarly as those who are now 16 and 17 years old, and when completing *Bachillerato* as those who are now 18 to 20. It is precisely what we find with the EPA data (Carabaña, 2013).

Note, in short, that the comparison we propose does not require equal treatment of students by schools, as we are interested in the quantity, but not the quality (it does not matter, therefore, that some of the students in cohort 17 were still studying under the LGE).

We begin estimating the effects of all non-compulsory education, separating in cohort 19 those who, born in 1994 and 1995, had just left school, from those who plann to continue, and comparing them respectively with the older groups who left at the same age and those who did actually continue. Table 2.10A shows greater differences between youths aged 16 to 30 years who left school before the age of 17 than among those who continued studying after that age. In the regression of Table 10B, the interaction between age and continuing education (the S of the equation (2) is introduced simply as a *dummy*) is negative and higher than half a point, although not statistically significant. It seems then, that continuing in school after the age of 16 adds nothing to the increase in PLP that other experiences cause in the young.

Table 2.10. PIAAC Literacy by Birth Cohorts and Continuing Education after the age of 16

A. AVERAGES, CASES AND SD					
			SCHOOLING AFTER 16		TOTAL
			DOES NOT CONTINUE	CONTINUES AFTER 16	
Literacy scale score - Plausible value 1	C17/81-85	AVERAGE	241.546	272.945	268.064
		CASES	67.000	364.000	431.000
		STAND, DEV,	34.725	40.691	41.383
	C18/86-90	AVERAGE	230.822	272.895	268.158
		CASES	51.000	402.000	453.000
		STAND, DEV,	40.232	42.630	44.368
	C19/91-93	AVERAGE	218.034	264.957	261.442
		CASES	23.000	284.000	307.000
		STAND, DEV,	44.998	40.077	42.239
	C19/94-95	AVERAGE	226.427	261.024	257.640
		CASES	18.000	166.000	184.000
		STAND, DEV,	54.415	34.331	38.000
	TOTAL	AVERAGE	232.993	269.436	265.222
		CASES	159.000	1216.000	1375.000
		STAND, DEV,	41.066	40.628	42.302

B. REGRESSION							
Model		Non-standardised coefficients		Standardised coefficients	t	Sig.
		B	Standard error	Beta		
1	(Constant)	204.808	6.901		29.678	.000
	AGE	1.182	.256	.119	4.611	.000
	SCHOOLING AFTER 16	37.925	3.421	.287	11.087	.000
2	(Constant)	192.895	17.580		10.972	.000
	AGE	1.682	.725	.170	2.320	.021
	SCHOOLING-AFTER-16	51.452	18.675	.389	2.755	.006
	AGE*SCHOOLING-AFTER-16	-.571	.775	-.111	-.737	.461

a, Independent variable: Literacy scale score - Plausible value 1

b, Only those cases where ABANDONDO (LEFT SCHOOL) >= A18 were chosen

This result is not very robust for several reasons. One being that the percentage of those leaving school before the age of 17 diminishes from 15% to 10% between cohorts 17 and 19; one might think that this 10% dropping out now should have a worse PLP than the previous 15%, due to a higher negative selection. To clarify this uncertainty, we repeated the estimate cutting off at age 17 and 18, when dropouts are approximately 20% in all cohorts, with the same results as cutting off at 16.

Another indication of limited robustness is that while normally age and experience have diminishing effects on cognitive capabilities, the small sample of those dropping out of school improves in a statistically significant way right between the age of 26 to 30, but not before. And, in fact, if we remove this cohort 17 and limit the comparison to cohort 18, interaction between age and continuing education after 16 becomes positive; but is still small and statistically insignificant[9].

In summary, although we must admit the cases are limited and the results are not very robust, it is not rash to construe that PLP scores improve with age and experience, but not with schooling. The difference between students who continue studying and those who do not (around 40 points) would all be the result of the (self) selection that takes place at the age of 16 when completing compulsory education.

We tried to confirm the soundness of this result, while specifying it, dividing this factor of overall selection of 40 points between the various levels possible for continuing education after the age of 16. For this we used the PIAAC information on highest level of education started (ESTUE). There are three optionss: continuing in ESO, if not completed, and if completed, one can choose between CFGM or Bachillerato. We have already seen that the FPI-CFGM students in the PIAAC sample are few and uncertain, so the most reasonable approach

[9] Observing generation by generation, we find it is only the 16-year-olds who increase the inital score. This could be because at this age there is still uncertainty about dropping out, but not being able to verify this, we have considered the score correct and have kept them as base.

is to combine them with Bachillerato (in any case, we checked that the results were the same without them).

Table 2.11. Years of school and PIAAC Literacy by Educational Level Started. Cohorts 15 to 17

A. AVERAGES, CASES AND SD						
			EDUCATION LEVEL STARTED, TO INTERMEDIATE			TOTAL
			LEFT 16	EGB-ESO	MORE	
Literacy scale score - Plausible value 1	C17/81-85	AVERAGE	241.5	247.0	277.3	268.1
		CASES	67	52	312	431
		STAND, DEV,	34.7	42.4	38.8	41.4
	C18/86-90	AVERAGE	230.8	226.4	280.6	268.2
		CASES	51	57	345	453
		STAND, DEV,	40.2	40.6	37.8	44.4
	C19/91-93	AVERAGE	218.0	231.3	272.0	261.4
		CASES	23	49	235	307
		STAND, DEV,	45.0	44.3	35.4	42.2
	C19/94-95	AVERAGE	226.4	237.3	266.7	257.6
		CASES	18	32	134	184
		STAND, DEV,	54.4	31.0	32.7	38.0
	TOTAL	AVERAGE	233.0	235.1	275.8	265.2
		CASES	159	190	1026	1375
		STAND, DEV,	41.1	41.2	37.2	42.3

B. REGRESSION						
Model		Non-standardised coefficients		Standardised coefficients	t	Sig.
		B	Standard error	Beta		
1	(Constant)	208.148	6.499		32.027	.000
	AGE	1.042	.242	.105	4.315	.000
	ESO	3.911	4.105	.032	.953	.341
	BUP MORE	44.016	3.251	.453	13.538	.000
2	(Constant)	192.895	16.547		11.657	.000
	AGE	1.682	.683	.170	2.465	.014
	ESO	17.882	21.944	.146	.815	.415
	BUP MORE	62.009	17.782	.638	3.487	.001
	AGE*ESO	-.582	.935	-.107	-.622	.534
	AGE*BUP MORE	-.761	.739	-.189	-1.030	.303

a, Independent variable: Literacy scale score - Plausible value 1

Source: PIACC data

Table 2.11A shows the PLP of 16 and 17-year old students (cohort 19/94-95) continuing in ESO or studying Bachillerato-CFGM (there are 7 precocious students who have already finished). Although they are the same age, there is a difference of 0.5 years of schooling between each group. As shown, students who continue in ESO are no different from those dropping out of school at 16; it is only among those who choose BUP –subject to having finished ESO- and the rest where there is the 40-point difference we have already seen, which is difficult not to attribute to self-selection of those continuing post-compulsory education.

We assume now that this is the same situation for 18 to 20-year-old students when they were 16 and 17 (quite a realistic assumption, as we have said). According to Table 2.11A, neither having continued studying ESO nor having continued studying Bachillerato-CFGM increased their PLP[10]. Group by group:

- Students who chose to continue in Bachillerato-CFGM have a PLP around 40 points higher than those who dropped out at 16 or continued in ESO. However, once this level of education was started, neither finishing them (as most have already done in the cohort 19/91-93), nor continuing with higher education (the majority in cohorts 18 and 17) increased their PLP more than not continuing education.
- Continuing in ESO instead of dropping out at 16 has little to do with the PLP. When making the decision, those choosing to drop out and those insisting on finishing ESO have the same PLP. The same is true later. The insistence on attaining an ESO certification does not appear to have any effect on the PLP in cohorts 18 and 17, in spite of the two years spent on average on this endeavour. The differences of about 10 points observed are not representative with such small samples. This result reinforces what we observed earlier for additional years of schooling in Basic Education.

Let us now check, following the same method, whether any of the three modes of higher education (after the LOGSE this included Advanced VET together with Diplomas and Degrees) escapes the inefficiency that Table 2.11 suggests for the whole. (I am using the terms prior to the current ones because they are the ones which still prevail in the cohorts analysed, although this issue is questionable in cohort 19).

Table 2.12A displays students who started Bachillerato according to the level of education they continued in. It leaves out those born in 1994-95, since at that age there was still a single group of students of Bachillerato with an average of 267 points (Table 2.11A); it is their peers born in 1991-93 who are now in four different schooling situations. Some continue trying to finish FPI or Bachillerato (if they have not dropped out), most have finished and have chosen one of the three paths available. As shown, both the selection made by the school to finish Bachillerato and the self-selection of the students themselves is quite strong. Those who were not able to finish have an average of 253 points. Those choosing FPII- CFGS are 13 points above them, those starting a Bachelor's Degree 34 points, those starting an 5-year Degrees 40 points. If we think about it, they seem to break the pattern, as they only exceed by 5 points those who chose a Bachelor's Degree[11].

10 The decrease in relation to those who dropped out at age 16 only has 53% probability of creating an actual difference, according to the regression of Table 11B.

[11] There are only 13, and it is unlikely that they have already been able to actually choose a master, so it must be the surviving 5-year degrees.

Table 2.12. PIAAC Literacy by Birth Cohorts and Continuing Education after the age of 16

A. AVERAGES, CASES AND SD							
			EDUCATION LEVEL STARTED				TOTAL
			FP1-BACH	CFGS-FPII	UNI1	UNI2	
Literacy scale score - Plausible value 1	C17/81-85	AVERAGE	254.1	274.1	286.2	294.2	277.3
		CASES	91	56	64	101	312
		STAND, DEV,	39.1	36.8	32.6	32.5	38.8
	C18/86-90	AVERAGE	259.1	269.8	289.8	300.8	280.6
		CASES	95	65	91	94	345
		STAND, DEV,	37.4	31.6	30.5	35.3	37.8
	C19/91-93	AVERAGE	253.5	267.1	287.9	293.3	272.0
		CASES	74	61	87	13	235
		STAND, DEV,	33.4	33.1	31.0	26.5	35.4
	TOTAL	AVERAGE	255.8	270.2	288.2	297.1	277.2
		CASES	260	182	242	208	892
		STAND, DEV,	36.9	33.7	31.1	33.5	37.7

B. REGRESSION						
Model		Non-standardised coefficients		Standardised coefficients	t	Sig.
		B	Standard error	Beta		
1	(Constant)	250.663	7.696		32.571	.000
	AGE	.217	.315	.022	.687	.492
	FPII	14.559	3.286	.156	4.430	.000
	UNI1	32.628	3.045	.385	10.714	.000
	UNI2	40.995	3.209	.460	12.773	.000
2	(Constant)	242.291	12.968		18.683	.000
	AGE	.574	.545	.057	1.052	.293
	FPII	14.190	20.617	.152	.688	.491
	UNI1	48.722	18.847	.575	2.585	.010
	UNI2	64.513	23.240	.724	2.776	.006
	AGE*FPII	.023	.877	.006	.026	.979
	AGE*UNI1	-.697	.808	-.190	-.864	.388
	AGE*UNI2	-.957	.934	-.274	-1.024	.306

a, Independent variable: Literacy scale score - Plausible value 1

Source: PIACC data

The same as before following ESO, these differences cannot be attributed to anything other than the selection processes, as they occur without the new levels of education having had time to have an impact. In any case, the effect of starting them cannot have been too large, at least if judged by what seems to produce their continuation (and possible completion) in cohorts 18 and 17, which is practically nil. (This assertion is valid for 5-year Degrees, even when in cohort 19 almost no one has started them, for in cohorts 18 and 17, when they already include half of the students, their distance with 3-year university diplomas –not yet Bachelor's Degrees- is maintained in about 10 points). Table 2.12B shows once more that there is no statistically significant difference between following each type of education, although if any group improves less it is in any case the one going to University.

DISCUSSION

We have managed to come up with estimates of the effect of the years of school on PLP. A simple regression with all the subjects has given us a coefficient close to 6. An analysis of the differences between age cohorts has reduced it to 5. This estimate on the variation between the cohorts coincides approximately with the results of the variation within cohorts. These estimates reflect the importance of an average year of schooling, but they do not say much about whether elementary education is more important than the rest.

Combining the separation by birth cohorts and by levels of education does not shed any light either on the years of Basic Education, due to the usual selection problem: as the cohorts are younger, those not completing Basic Education have more years of schooling, but they have also suffered a stronger negative selection. However, for the post-compulsory years, Tables 2.7 and 8 suggest rather small or no effects. The fact that no effect is observed from the rise in the years of basic education in the younger cohorts suggests that the years these students spend in obtaining a certificate - that is, from year eleven on- are inefficient. All the increases undergone by the other levels of education along history also seem inefficient, even considering- not much, probably, given the size of the sample and how sudden the change was- the exception of FPII.

As it is not possible to directly examine basic education, it is very important to confirm the lack of effect of further education. The strategy of attributing to selection the differences between levels and estimating the effect of the years of school at each level coincides in essence with the above–very low effect– in Basic Education and in Bachillerato, but not at the three higher levels. Here we obtained coefficients of 2 and 3 PLP points per year of school, certainly lower than the average coefficient of 5 points, and therefore formally consistent with the hypothesis of decreasing returns, but inconsistent with that seen in cohorts 18 and 19 and with experience.

Indeed, it would be wrong to interpret these coefficients as an indication that the years of university continue increasing PLP. What this really means is that what increases PLP is the years students delay completing their education, even after the age of 30. Delaying completion of education is something frequently regretted, to which high costs and no benefits are attributed and which is attempted to be remedied by disputed ways. If it were true that every year of delay increases PIAAC competencies by 3 points, perhaps we would see it more positively. A detailed analysis of the data–far too detailed to report it here– suggests that being enrolled in University does not increase competency levels as much. Two selection factors seem to inflate coefficients. One is that the more selective branches of study –which PIAAC covers without much detail– have longer careers *de facto* and *de jure*, for example, technical careers. Another one is that many students are not delayed due to incompetence, but for other reasons, such as work (unlike those continuing in EGB and Bachillerato). Also, there are flaws in the measurement of the years of schooling.

Fortunately, in the youngest cohort, we see the effects of selection with hardly any contamination from the effects of schooling. Also, we know for certain from PISA that the immediately older birth cohorts had the same competencies as this younger one at age 15, and that they are distributed in similar proportions among the levels of education. Finally, combining the division by levels of education with the division by birth cohorts we can overcome the defects of estimating the years of schooling. This procedure, which seems clearly superior to the others, achieves results close to zero.

How can we match such low estimates for the years of post-compulsory schooling with the estimate of 5 PIAAC points per year of schooling derived from the variation between the older cohorts? The most obvious way is to attribute the average effect to primary, or elementary education, that is, to the first eight years of schooling, according to the initial hypothesis. At the start of the second half of the 20th century, many children stayed below those levels of education, which left their potential PLP underdeveloped. In the second half of the 20th century, elementary education became universal. Those were the years of schooling that led to an increase in PLP, and at the same time to a decrease in inequality and an increase in its correlation with the years of school, abovementioned. From cohort 15, already in the fourth quarter of the 20th century, all children have been subject to those years of school that develop PLP; further schooling, , albeit small, has been limited to the years of post-compulsory education, with limited or no impact on PLP.

The finding that post-compulsory education has no or almost no effect is limited so far to the PIAAC literacy scores. It is easy to confirm it is also valid for PIAAC numeracy scores. It is, however, obvious that it does not hold for the specific competencies taught in Upper Secondary Education and University.

The results are also limited for now to Spain, although there are precedents indicating that the PIAAC data will provide similar results in other countries.

CONCLUSIONS

The starting point of this study is the consensus, shared expressly by those responsible for literacy teaching, that this is not acquired only at school. By analogy with the IQ, with which literacy is closely related, we proposed the hypothesis that the first years of schooling are more important than the following ones, whose effects soon become irrelevant, and we tried to confirm the hypothesis with PIAAC 2012 data for Spain. To solve the problem of identification generated by the interactive (or not recursive) relationship between schooling and literacy, we analysed two situations where they seem to vary independently, the date of birth and levels and modes of education.

The results of the various analyses conducted seem to support the initial hypothesis. By examining birth cohorts we found that a year of schooling generated in the third quarter of the 20th Century an increase of 5 points in the PIAAC literacy test score. More or less 5 points were also the result of estimating a simple regression equation in the birth cohorts that have completed their education. It has not been possible to estimate separately the importance of elementary education, but through three different paths we have come to the finding that the effects of post-compulsory education are less than this overall mean. . One, the least reliable, attributes to each year of non-compulsory education a maximum effect of 3 points. The other two, one clearly superior to them all because it is based on scores observed before schooling, reach the conclusion that the effect of continuing after compulsory schooling, including continuing in basic education, is nil or very small. The most obvious conciliation for these diverging estimates is assuming that most of the effect, if not all of it, is generated in the first years of school.

These results are in line with the psychological theories of development and learning upon which literacy tests were designed, and with the theories of reading proficiency development, with the official definition of literacy itself and with a great part of the empirical literature. This last coincidence rules out in any case that we the results are due to a peculiarity of Spanish schools.

Finally, we should clarify that the inefficiency of post-compulsory schools in the general competencies of the kind measured by the PIAAC tests has certain political importance, as it discredits the claim that they should foster them.

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3. The Economic Effects of Education in Spain: an approach with PIAAC data

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3. THE ECONOMIC EFFECTS OF EDUCATION IN SPAIN: AN APPROACH WITH PIAAC DATA[1]

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ABSTRACT

The recent literature shows the importance of the economic effects of human capital, yet emphasizes the role of effectively acquired skills and knowledge beyond the amount of time spent in the education system and the educational levels completed. In this study we use PIAAC data to analyze, using econometric techniques, the effect of education on the labour behaviour and results of individuals in terms of wages, probability of participating in the labour market and probability of being employed. The results obtained show, *ceteris paribus*, a significant positive effect of both educational levels completed and the PIAAC scores. This suggests the usefulness, without neglecting the quantitative aspects, of making efforts to increase the quality of education in order to exploit the full potential of the investment in education in Spain. The study provides some simulations with different improvement scenarios and their associated potential gains in terms of activity, unemployment and labour productivity.

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Keywords

Human Capital, Quality of Education, PIAAC, Productivity, Unemployment.

INTRODUCTION

Spain allocates a significant amount of all types of resources, both from the public sector as well as from families and the students themselves, to the educational system. This effort makes more sense inasmuch as it is expected that the sacrifice made in the present will allow us to reap a number of benefits for society in general in the future, and especially for the individuals who receive education. So, from the point of view of economics, education can be considered as an investment whose profitability will depend heavily on the economic effects of education in terms of a better and more intense employment career for graduates.

Thanks to better educational training students become more capable, more productive and more attractive workers for firms. This increases their employability, reduces the likelihood of being unemployed if looking for a job, promotes integration into the labour market with better conditions and provides higher wages throughout their working life. Consequently, education can also lead to a greater likelihood of actively participating in the labour market since increasing the benefits associated with being employed, or trying to be, would be more attractive.

The theory of human capital, conceived at the beginning of the second half of the last century with decisive contributions such as those of Schultz (1960) and Becker (1964), starts out with the behaviour of rational individuals who make decisions regarding their education in order to try to achieve the best situation for them throughout their lives. This theory postulates that the individual values the expected future benefits of education and also the associated costs, monetary or otherwise. According to this view, education is clearly an investment and its results are a type of capital, human capital, which has the characteristic of being embodied in its owner. Naturally, the human capital of a worker also depends on factors other than formal education that will influence productivity, such as work experience or training acquired in the firm itself. However, formal education received in the educational system would be a fundamental determinant of the human capital of workers anyway.

The literature on the determinants of wages, following the analytical framework of wage equations postulated by Mincer (1974), offers extensive evidence favourable to the positive effect of educational training. Card (1999), Harmon et al. (2003) and Heckman et al. (2006) give a very complete overview of this type of analysis. Similarly, the data regularly show activity rates increasing and unemployment rates decreasing with the level of education, both in Spain and in other countries. In the case of Spain, Pastor et al. (2007 and 2010), de la Fuente and Jimeno (2011) and Pérez García et al. (2012) show that these positive relationships are robust to the effect of other socio-demographic variables which could be related to the educational level.

All of these studies point to the importance of the amount of education as a component of human capital and its positive economic effects in terms of wages, participation in the labour market and unemployment. However, a certain amount of education, i.e.: years of schooling, may not always lead to a similar amount of human capital and in this case, its economic effects would not be expected to be the same either. Thus, if the education system is not working properly, education will mean less training and less human capital than might be expected, so that those positive effects would be reduced and may even disappear. For example, the PISA results for Spain (Program for International Student Assessment) suggest that there are problems in the Spanish educational system and that Spain's educational performance can be improved with regard to other countries. Students in Spain show lower levels of knowledge at the end of compulsory education (lower secondary education). Data on unemployment rates, wage levels and over-education suggest that the other levels of education could be affected by similar problems of educational performance.

Therefore, it would not be the formal years of schooling that would increase the individual's human capital but effectively acquired knowledge and skills, generating the benefits indicated. Aspects such as the quality of education would be decisive and an increase in the years studied on its own could even be irrelevant.

The most recent literature on human capital and economic growth points in that direction. Hanushek and Woessmann (2008 and 2011) and OECD (2010) show the importance of human capital in economic growth, but they emphasize the role of effectively acquired skills and knowledge and not just the amount of time spent in the education system. Human capital is very relevant when explaining the differences in long-term growth of the per capita income of countries, but it is the educational outcomes that are important. After including the data from PISA reports and other evidence of a similar nature, the variables of the amount of schooling are no longer significant. Hanushek and Woessmann interpret this loss of significance in the sense that schooling on its own has no effects beyond its impact on the knowledge and skills of individuals. Therefore, more schooling would not contribute anything if it did not involve greater knowledge and skills.

There is also evidence on the impact on subsequent labour achievements of the scores obtained by students in the tests carried out. Mulligan (1999), Murnane et al. (2000) and Lazear (2003) show a positive effect of some results in tests of numeracy skills on wages. Equally positive evidence is obtained by Denny et al. (2000) and McIntosh and Vignoles (2001) for the UK, and Finnie and Meng (2002) and Green and Riddell (2003) for Canada. The same type of results is obtained using the data on the results from knowledge and skills tests for adults. Denny et al. (2004) and Hanushek and Zang (2009), using data from the International Adult Literacy Survey (IALS), found for a sample of countries that knowledge and skills have a significant positive impact on wages and, once that is taken into account, the wage returns on the amount of education (i.e.: years of schooling) decrease substantially, almost by a fifth. Kahn (2004) provides evidence in favor of the hypothesis that knowledge has a significant effect on the probability of employment.

The proper analysis of these issues requires good statistics that include both individual data on knowledge and skills, as well as on other personal characteristics such as educational level and employment situation and results. In the Spanish case the lack of statistical sources on knowledge and skills of individuals has been a serious obstacle, not to mention the total lack of databases which combine all the information mentioned above.

This precarious situation has been conditioned by the late and partial participation of our country in the studies carried out on these issues at an international level. Until recently Spain only participated in PISA studies, which refer to the particular situation of a specific population cohort in its final year of compulsory education. However, it did not participate in any of the studies carried out on these issues for the whole adult population, neither in the successive International Adult Literacy Surveys (IALS) conducted between 1994 and 1998, nor in the Adult Literacy and Life-skills Survey of 2003. This has meant a clear limitation for obtaining results about the economic effects of education in Spain and on the role played by aspects related to its quality. Despite this, studies from the PISA data suggest that there are obstacles which stand in the way of formal education fully being able to generate an increase of human capital in our country, Serrano (2012). Empirical studies dealing with wage returns on education in Spain, despite confirming that there is a positive and significant effect, present a disturbing situation, with a progressive fall in the estimated profitability of education. In Pérez et al. (2012), for example, it is estimated that an additional year of study means an increase of 6.3% in wages, with a fall of 2.3 points compared to 1995; in De la Fuente and Jimeno (2011) 6.1%; in Raymond (2011) 6.9% with a fall of 1.8 points; and in Murillo, Rahona and Salinas (2010) 7.4% with a fall of 2.4 points. Pastor et al. (2007 and 2010) already estimated a fall of almost one percentage point between 1995 and 2002. In Felgueroso, Hidalgo and Jimenez's (2010) work, based on the Social Security micro data, a drop in the graduate wage bonus since the mid-eighties is estimated.

Fortunately, the situation has changed radically in terms of the information available, with the full participation of Spain in the Programme for the International Assessment of Adult Competencies (PIAAC) of the OECD. The information from this study provides the possibility, also for the case of Spain, of accessing individual data on knowledge, education levels and a very broad set of variables, including those related to the labour market or income, among others.

The PIAAC data open up the possibility of analyzing the impact of the knowledge and skills of the population. PIAAC provides a wealth of information about the individuals' labour situation and their educational level, but also about the knowledge and skills of those same individuals. The last aspect is a fundamental innovation and opens the door to the analysis of the economic effects of the quality of education.

This study aims to address these issues in the case of Spain. To do this, firstly we discuss the data and methodology to be used and we examine the relationship between the data on educational levels completed and on knowledge and skills. Then we apply econometric techniques to individual PIAAC data to analyze the probability of participating in the labour market and of being employed, as well as the determinants of wages. In these analyses, along with the usual variables from previous studies on the Spanish case concerning the educational levels completed, we also include variables of knowledge and skills. From these results, we consider some scenarios about potential earnings linked to various improvements in these areas for the adult population in Spain, in terms of participation in the labour market, unemployment and productivity. Finally we present the main conclusions.

METHODOLOGY AND DATA

Our aim is to analyze the economic effects of education in Spain, particularly those relating to employment achievements of individuals. To do this, we are going to consider the decision to participate in the labour market (activity), the probability of employment (employability and unemployment) and wages (productivity).

The procedure will be to set out specifications in order to explain these issues, including as determinants the maximum level of education attained as well as other variables related to equally important personal characteristics such as gender, age or the work experience and nationality of the individual.

In the analysis of participation in the labour market and the probability of employment, *probit* models are estimated to simultaneously analyze the effect of each variable on the topic of interest. In the case of participation a *probit* is estimated for the population of working age where the dependent variable takes the value 1 for active (employed or unemployed) and 0 for inactive. In the case of employment probability the dependent variable takes the value 1 for employed and 0 for unemployed, controlling for possible sample selection bias by a Heckman-type equation of labour market participation. For greater clarity the marginal effects on the probability of each variable are provided directly. These results should be interpreted as the differential effects with respect to the reference individual which is always a Spanish male between 16 and 24 years old, with primary education at most, single and with no children.

In the analysis of wages, Mincerian type wage equations are estimated by OLS where the dependent variable is the logarithm of the wage per hour worked. Therefore the estimated coefficients can be interpreted as the relative variation of the wage associated with each variable in relation to the reference individual, which in this case is a Spanish male with primary education at most.

In all the analyses the data come from individual PIAAC surveys and the Jackknife 2 resampling procedure has been used to estimate the standard errors for 80 multiple samples as well as for the full sample.

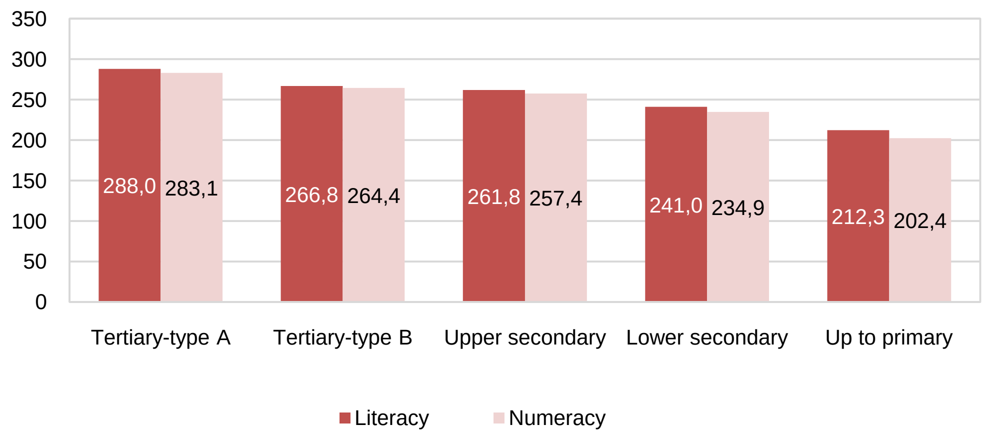
In the analysis of the participation in the labour market we include as explanatory variables, together with those relating to the educational level of the individuals and their score in PIAAC, also other variables referring to the gender, nationality, work situation of the partner (employed, unemployed, student, disabled, etc.) and number of children, which may also influence the individual's decision to work.

In the case of the PIAAC scores we explore the effect of the literacy and numeracy scores separately as well as together.[2]

EDUCATIONAL LEVELS AND PIAAC SCORES

The PIAAC results according to educational levels indicate that in Spain there is a clear positive association between the highest level of education completed by the individual and the results in literacy and numeracy skills. Graph 3.1 and Table 3.1 illustrate the situation for the working population.

Graph 3.1. PIAAC score in literacy and numeracy for the employed, according to levels of education



Note: average of the 10 plausible values from PIAAC.
Source: PIAAC and authors' calculations.

Table 3.1. Structure according to levels of study of the employed, located in the 6 performance levels from PIAAC

	Literacy						Numeracy					
	N<1	N1	N2	N3	N4	N5	N<1	N1	N2	N3	N4	N5
Up to primary	51.1	27.2	15.9	4.7	0.6	.	46.4	28.1	14.0	4.3	0.7	.
Lower secondary	28.9	35.3	26.4	14.2	3.7	.	35.3	33.1	26.2	12.7	4.5	.
Upper secondary	13.7	23.3	27.1	23.9	13.6	9.4	13.1	23.4	26.4	24.1	19.6	.
Tertiary-type B	0.9	7.7	10.0	12.6	7.1	.	1.9	7.2	11.3	11.2	9.5	.
Tertiary-type A	5.4	6.5	20.7	44.5	75.0	90.6	3.2	8.3	22.1	47.8	65.6	100.0
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

PIAAC Levels: <1 (less than 176 points), 1 (176-225 points), 2 (226-275 points), 3 (276-325 points), 4 (326-375 points), 5 (376-500 points).
Source: PIAAC and authors' calculations.

The Spanish on average get better scores the higher their educational level is. This improvement is gradual and systematic with each of the successive levels of education, from primary education to

[2] The econometric analyses are based on the first plausible value of the test of numeracy and literacy.

university degrees. Furthermore, it occurs in the two key areas under assessment in the Spanish case: literacy and numeracy. Looking at the structure according to the PIAAC performance levels, we see clear differences that reinforce the pattern shown. Thus, among the university graduates more than 50% are at PIAAC level 3 or above. By contrast, the population with only primary education is at the opposite end. Within this group barely 50% reaches PIAAC level 1 at most.

Without a doubt these two aspects are interrelated. On the one hand, the greater the ability of the person, the easier it will be to progress in the educational system and achieve a greater educational grade. On the other, given an innate ability, the more a person progresses in terms of levels of education the better will be their chances of increasing their knowledge and skills.

Therefore, taking into account this complex interrelationship, in the empirical analysis presented and discussed below we set out specifications that include only the educational level variable, only the knowledge variable and, finally, both simultaneously. Undoubtedly, some of the differences observed in the PIAAC scores will be due to differences in innate abilities prior to education. However, we consider that the estimated effect for that variable, once it is also controlled by the educational level of the person, is also a good indicator of the effect of increases in that variable which are related to education.

PARTICIPATION IN THE LABOUR MARKET

The results in Table 3.2 show the marginal effects relating to the probability of participating in the labour market. Amongst the socio-demographic characteristics the roles of gender and age stand out, while those relating to nationality, the work situation of the partner and the number of children are not significant. Everything else being constant, being female reduces the probability of being active by more than 10 points. Being over 25 years old means a substantial increase in participation, around 25 points, although this increase loses most of its strength at the end of the working life (between 55 and 65 years).

Regarding the effect of education, the results in column 1 show a significant positive effect of education, increasing with each additional level of education attained. Thus, with everything else constant, having completed compulsory education (lower secondary education) means there is 7 points higher probability of participating compared to not having done so. This increase reaches 20 points in the case of having university education. These results confirm the strong association between more education and more activity shown in other previous studies based on other statistical sources for the Spanish case, such as Pastor et al. (2007).

By substituting the educational level variable with the PIAAC scores in literacy (column 2) or numeracy (column 3) we can see that there is a significant and positive relationship between the level of knowledge of the individual and their decision to participate in the labour market. By taking both types of skills into account simultaneously (column 4) the positive effects of literacy are no longer significant, but remain so in the case of numeracy. This result is not surprising given the expected positive relationship between better literacy and greater numeracy skills, two key dimensions of a higher level of human capital. In any case it turns out to be a first indication of the special weight of the latter in the area of employment. The difference between having reached the higher levels of PIAAC (levels 4 and 5) and being at the lowest level (level <1) reaches 19 percentage points of the probability of being active.[3]

Table 3.2. Marginal effects of the probability of participation in the labour market

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ref: Man	Woman	-0.1398 ***	-0.1270 ***	-0.1185 ***	-0.1176 ***	-0.1379 ***	-0.1330 ***	-0.1309 ***
		(0.0120)	(0.0118)	(0.0121)	(0.0121)	(0.0123)	(0.0126)	(0.0126)
Ref: National	Foreigner	0.0119	0.0313 *	0.0344 *	0.0338 *	0.0193	0.0243	0.0224
		(0.0191)	(0.0185)	(0.0189)	(0.0187)	(0.0191)	(0.0197)	(0.0195)
Ref: 16-24 years	25-34 years	0.2507 ***	0.2757 ***	0.2754 ***	0.2754 ***	0.2524 ***	0.2535 ***	0.2531 ***
		(0.0127)	(0.0116)	(0.0117)	(0.0117)	(0.0125)	(0.0125)	(0.0126)
	35-44 years	0.2522 ***	0.2801 ***	0.2789 ***	0.2787 ***	0.2548 ***	0.2558 ***	0.2547 ***
		(0.0165)	(0.0156)	(0.0155)	(0.0155)	(0.0161)	(0.0160)	(0.0161)
	45-54 years	0.2239 ***	0.2484 ***	0.2500 ***	0.2498 ***	0.2278 ***	0.2303 ***	0.2293 ***
		(0.0160)	(0.0152)	(0.0152)	(0.0152)	(0.0158)	(0.0157)	(0.0158)
	55-65 years	0.0477 *	0.0874 ***	0.0886 ***	0.0876 ***	0.0577 **	0.0623 **	0.0584 **
		(0.0246)	(0.0243)	(0.0247)	(0.0246)	(0.0244)	(0.0245)	(0.0246)
Ref: No partner	Employed full-time	0.0296	0.0378 **	0.0335 *	0.0336 *	0.0272	0.0248	0.0249
		(0.0186)	(0.0186)	(0.0189)	(0.0189)	(0.0185)	(0.0187)	(0.0187)
	Employed part-time	0.1199 ***	0.1243 ***	0.1229 ***	0.1230 ***	0.1186 ***	0.1176 ***	0.1177 ***
		(0.0239)	(0.0250)	(0.0248)	(0.0248)	(0.0242)	(0.0242)	(0.0241)
	Unemployed	0.0184	0.0152	0.0051	0.0036	0.0195	0.0150	0.0112
		(0.0257)	(0.0266)	(0.0271)	(0.0269)	(0.0255)	(0.0257)	(0.0256)
	Student	0.1196	0.1580	0.1473	0.1457	0.1240	0.1212	0.1158
		(0.2794)	(0.2062)	(0.2255)	(0.2282)	(0.2694)	(0.2733)	(0.2822)
	Apprentice	-0.4137 **	-0.3111 *	-0.3434 *	-0.3463 *	-0.4081 **	-0.4159 **	-0.4253 **
		(0.1992)	(0.1777)	(0.1821)	(0.1824)	(0.1941)	(0.1938)	(0.1953)
	Retired	-0.1936 ***	-0.2073 ***	-0.2054 ***	-0.2048 ***	-0.1968 ***	-0.1977 ***	-0.1961 ***
		(0.0417)	(0.0430)	(0.0424)	(0.0425)	(0.0422)	(0.0419)	(0.0419)
	Perm. Disability	-0.0374	-0.0637	-0.0509	-0.0486	-0.0443	-0.0420	-0.0354
		(0.0813)	(0.0880)	(0.0862)	(0.0859)	(0.0832)	(0.0830)	(0.0817)
	Domestic tasks	-0.0175	-0.0231	-0.0272	-0.0276	-0.0185	-0.0209	-0.0220
		(0.0301)	(0.0306)	(0.0307)	(0.0307)	(0.0300)	(0.0301)	(0.0301)
	Others	-0.1090	-0.1063	-0.1130	-0.1131	-0.1131	-0.1173	-0.1173
		(0.0921)	(0.0898)	(0.0931)	(0.0934)	(0.0925)	(0.0941)	(0.0947)
Ref: No children	1 child	0.0083	-0.0004	-0.0009	-0.0013	0.0095	0.0096	0.0088
		(0.0259)	(0.0263)	(0.0263)	(0.0264)	(0.0257)	(0.0257)	(0.0258)
	2 children	0.0088	-0.0082	-0.0083	-0.0087	0.0094	0.0091	0.0084
		(0.0245)	(0.0249)	(0.0247)	(0.0248)	(0.0244)	(0.0243)	(0.0244)
	3 children	-0.0294	-0.0553 *	-0.0524	-0.0525 *	-0.0295	-0.0292	-0.0290
		(0.0304)	(0.0321)	(0.0316)	(0.0315)	(0.0306)	(0.0304)	(0.0303)
	4 or more children	-0.0331	-0.0634	-0.0562	-0.0563	-0.0313	-0.0292	-0.0289
		(0.0368)	(0.0383)	(0.0377)	(0.0378)	(0.0366)	(0.0363)	(0.0363)
Ref: Up to primary	Lower secondary	0.0704 ***				0.0632 ***	0.0564 ***	0.0570 ***
		(0.0153)				(0.0161)	(0.0167)	(0.0166)
	Upper secondary.	0.0948 ***				0.0819 ***	0.0702 ***	0.0713 ***
		(0.0164)				(0.0185)	(0.0192)	(0.0191)
	Tertiary-type B	0.1484 ***				0.1386 ***	0.1292 ***	0.1299 ***
		(0.0173)				(0.0187)	(0.0195)	(0.0194)
	Tertiary-type A	0.1990 ***				0.1838 ***	0.1718 ***	0.1747 ***
		(0.0147)				(0.0179)	(0.0180)	(0.0182)
	Literacy score		0.0010 ***		-0.0002	0.0003 **		-0.0004
			(0.0001)		(0.0003)	(0.0002)		(0.0003)
	Numeracy score			0.0012 ***	0.0013 ***		0.0005 ***	0.0009 ***
				(0.0001)	(0.0003)		(0.0002)	(0.0003)
	N	5951	5956	5956	5956	5951	5951	5951
	F	56.74	58.31	64.60	67.24	52.63	51.92	55.84

***, **, *: Significant at 1%, 5% and 10% respectively. Standard errors in parentheses, calculated using the Jackknife2 replication procedure for 80 replicated weights. Source: PIAAC and authors' calculations.

[3] The results of the marginal effects of being active, taking into account the PIAAC performance levels instead of the scores, are not included in this paper but are available from the authors on request.

Columns 5-7 include both the two types of variables related to human capital: educational levels completed and PIAAC scores. The results show that both have significant positive effects on activity, whether it is the level of literacy or that of numeracy. That is, whatever the level of knowledge shown in PIAAC, the higher the educational level of the individual the greater is the probability of them participating in the labour market. Similarly, whatever the individual's educational level, a higher level of knowledge also increases this probability. The inclusion of the PIAAC variables, however, tends to reduce the effect attributed to the educational level, which now turns out to be approximately one tenth lower than that previously estimated without considering the information on the individuals' knowledge (column 1).

These results suggest that the human capital of the individual is a very important factor in the decision to participate in the labour market. Activity would respond positively to a greater amount of education (years of schooling of the individual), but the intensity of that response would substantially increase with the effectiveness of this education, and also with the quality of education and the knowledge and skills acquired through it. Thus, for example, given the educational levels completed by individuals, moving from level <1 to level 4 of PIAAC would mean about 12 additional points in the probability of being active.

PROBABILITY OF EMPLOYMENT

Table 3.3 shows the results from the analysis of the determinants of the probability of being employed. They are the results of estimating *probits* which incorporate a Heckman-type equation of participation which includes additional personal characteristics that were not included as explanatory variables in the specification of the probability of employment, such as the work situation of the partner. The results obtained with a simple *probit* of the probability of employment are similar.

Column 1 shows the results without including any PIAAC variable. The estimations obtained in this case indicate that there are no significant differences in the probability of employment linked to gender, while, *ceteris paribus,* that of foreigners would be 7 points lower than that of Spanish people. The coefficients by age cohort point to the existence of significant disparities, with a probability of employment which would register the minimum for the reference group of the 16 to19 years old people and would subsequently increase with age.

Table 3.3. Marginal effects of the probability of being employed

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ref: Man	Woman	-0.0024	0.0129	0.0214	0.0230 *	0.0019	0.0095	0.0115
		(0.0162)	(0.0131)	(0.0134)	(0.0136)	(0.0131)	(0.0132)	(0.0133)
Ref: National	Foreigner	-0.0701 ***	-0.0507 ***	-0.0430 **	-0.0445 **	-0.0559 ***	-0.0471 **	-0.0498 **
		(0.0261)	(0.0195)	(0.0205)	(0.0206)	(0.0199)	(0.0201)	(0.0201)
Ref: 16-24 years	25-34 years	0.1368 ***	0.1363 ***	0.1359 ***	0.1357 ***	0.1375 ***	0.1368 ***	0.1362 ***
		(0.0517)	(0.0181)	(0.0200)	(0.0208)	(0.0203)	(0.0204)	(0.0203)
	35-44 years	0.1656 ***	0.1633 ***	0.1611 ***	0.1596 ***	0.1689 ***	0.1670 ***	0.1643 ***
		(0.0564)	(0.0176)	(0.0197)	(0.0200)	(0.0198)	(0.0196)	(0.0197)
	45-54 years	0.1918 ***	0.1884 ***	0.1923 ***	0.1911 ***	0.1985 ***	0.2010 ***	0.1989 ***
		(0.0579)	(0.0191)	(0.0209)	(0.0211)	(0.0220)	(0.0214)	(0.0216)
	55-65 years	0.2255 ***	0.2462 ***	0.2501 ***	0.2475 ***	0.2393 ***	0.2433 ***	0.2384 ***
		(0.0869)	(0.0243)	(0.0251)	(0.0255)	(0.0346)	(0.0314)	(0.0331)
Ref: Up to primary	Lower secondary	0.0327 *				0.0210	0.0132	0.0150
		(0.0198)				(0.0165)	(0.0171)	(0.0174)
	Upper secondary.	0.1299 ***				0.1065 ***	0.0888 ***	0.0914 ***
		(0.0390)				(0.0198)	(0.0209)	(0.0208)
	Tertiary-type B	0.1372 **				0.1119 ***	0.0925 ***	0.0953 ***
		(0.0544)				(0.0287)	(0.0294)	(0.0295)
	Tertiary-type A	0.2075 ***				0.1704 ***	0.1465 ***	0.1531 ***
		(0.0702)				(0.0245)	(0.0242)	(0.0244)
	Literacy score		0.0011 ***		-0.0004	0.0005 ***		-0.0006 **
			(0.0001)		(0.0003)	(0.0002)		(0.0003)
	Numeracy score			0.0013 ***	0.0016 ***		0.0009 ***	0.0013 ***
				(0.0001)	(0.0003)		(0.0002)	(0.0003)
	N	5951	5951	5951	5951	5951	5951	5951
	F	8.48	19.52	22.32	17.47	14.58	16.90	16.70

***, **, *: Significant at 1%, 5% and 10% respectively. Standard errors in parentheses, calculated using the Jackknife2 replication procedure for 80 replicated weights.
Source: PIAAC and authors' calculations.

The educational level appears as a fundamental determinant of the probability of employment in Spain. The estimations obtained suggest that there would not be substantial differences between having lower secondary education and not having them, but the probability would increase significantly with the completion of upper secondary education. Having completed upper secondary education or tertiary-type B education (CFGS and FPII, Spain's professional training programmes) would mean 13 points higher probability of employment. A university degree would increase that difference beyond 20 percentage points.

When using alternative specifications without educational level variables and including PIAAC score variables (columns 2-4) the effects of other variables are maintained, while literacy and numeracy skills are shown as positive determinant factors of the probability of employment, the estimated effect being somewhat higher in the case of numeracy skills. By introducing both variables numeracy would maintain its positive effect, while the literacy variable would lose it.

By including both variables of educational level as variables of knowledge (columns 5-7), the results show the existence of positive effects on the probability of employment in both cases. Adding the score in literacy partially reduces the positive effects of upper secondary and university education (which drop to 11 and 17 points, respectively), but they maintain their significance. The effect of literacy would also continue to be significant, but its magnitude would be less than half of that estimated without including educational variables. The differences between reaching the highest levels of PIAAC (levels 4 or 5) or staying in the lowest (level <1) would be more than 11 percentage points.

In the case of numeracy skills something similar happens. The educational levels are still associated with significant differences in the probability of employment, but these differences are of lesser magnitude. They are now lower by up to a third compared to those estimated regardless of PIAAC scores. The numeracy variable itself would still be significant, though the effect is reduced by a third compared with the estimation without education variables. The difference between reaching the highest levels of PIAAC (levels 4 or 5) or staying in the lowest (level <1) would practically reach 20 percentage points.

When the two PIAAC scores (literacy and numeracy) are added to the education variables the educational levels turn out to be significant and with effects similar in magnitude to those obtained when considering only the numeracy scores. Numeracy continues to have a significant positive effect whose magnitude increases. In contrast, the trend of the effect of literacy becomes negative. A more detailed analysis of the probability of employment according to PIAAC levels indicates that, given a certain level of numeracy skills, the basic improvements in literacy (going from level <1 in this field to 1 or 2) are more significant than additional improvements. On the other hand, given a certain level of literacy, the most relevant improvements in numeracy skills for the probability of employment are those that refer to reaching higher levels in this area (level 3 or higher).

WAGES

Table 3.4 shows the results of wage equations that include variables relating to the personal characteristics of the worker as determinants. Education is included through the years of schooling variable and work experience is included through the PIAAC variable of years in paid work[4] and years in paid work squared. Column 1 corresponds to the standard case in which variables of the level of knowledge are not considered. The results of the effect of aspects such as gender and nationality are consistent with those usually obtained in these types of studies. With everything else constant, being a woman and being a foreigner have significant and substantial negative effects of 14% and 15% respectively compared to the case of men and workers of Spanish nationality. The individual's human capital has a significant positive effect on wages. Thus, the wage initially increases with years of work experience, but at a progressively less intense rate (picked up by the variable of experience squared). This profile is also consistent with previous literature on the subject. Meanwhile, the amount of education has a significant positive effect given that, *ceteris paribus*, each additional year of schooling means an average increase of 7.1% of wages. That rate of return on schooling is similar to that obtained in previous studies of the Spanish case from other statistical sources such as the

4 Wage regression exercises have also been carried out by substituting the variable of years of work with the variable of potential experience, calculated as age-years of education-6 (age-16 in the event that the previous specification gives as a result individuals who could have started to work before age 16). The results are very similar both for the coefficients of experience and for the other explanatory variables.

Wage Structure Survey. The results in Jimeno et al. (2013) for the Spanish case indicate that competencies increase with the level of education, while work experience is positively correlated with them only in the case of workers with less schooling.

Table 3.4. Wage regressions with years of study as an explanatory variable. Dependent variable: logarithm of wage per hour worked

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ref: Man	Woman	-0.1448 ***	-0.0713 ***	-0.0472 **	-0.0520 ***	-0.1284 ***	-0.1155 ***	-0.1155 ***
		(0.0182)	(0.0197)	(0.0194)	(0.0192)	(0.0184)	(0.0184)	(0.0183)
Ref: National	Foreigner	-0.1545 ***	-0.1040 ***	-0.0983 ***	-0.0919 ***	-0.1214 ***	-0.1140 ***	-0.1140 ***
		(0.0354)	(0.0329)	(0.0313)	(0.0317)	(0.0342)	(0.0332)	(0.0335)
	Exper.	0.0202 ***	0.0219 ***	0.0205 ***	0.0208 ***	0.0202 ***	0.0197 ***	0.0197 ***
		(0.0036)	(0.0037)	(0.0038)	(0.0038)	(0.0036)	(0.0036)	(0.0036)
	Exper.^{2}	-0.0002 **	-0.0003 ***	-0.0002 **	-0.0002 **	-0.0002 **	-0.0002 **	-0.0002 **
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	Years of study	0.0711 ***				0.0627 ***	0.0608 ***	0.0608 ***
		(0.0029)				(0.0035)	(0.0035)	(0.0036)
	Literacy score		0.0037 ***		0.0013 ***	0.0013 ***		0.0000
			(0.0003)		(0.0005)	(0.0003)		(0.0004)
	Numeracy score			0.0038 ***	0.0027 ***		0.0015 ***	0.0015 ***
				(0.0003)	(0.0005)		(0.0003)	(0.0004)
	Constant	1.1289 ***	0.9737 ***	0.9790 ***	0.9069 ***	0.8731 ***	0.8373 ***	0.8374 ***
		(0.0479)	(0.0845)	(0.0815)	(0.0872)	(0.0749)	(0.0752)	(0.0780)
	N	2506	2507	2507	2507	2506	2506	2506
	R^2	0.3023	0.1862	0.1976	0.2011	0.3114	0.3162	0.3162
	F	165.97	72.98	76.55	63.72	140.87	143.24	121.76

***, **, *: Significant at 1%, 5% and 10% respectively. Standard errors in brackets, calculated using the Jackknife2 replication procedure for 80 replicated weights.
Source: PIAAC and authors' calculations.

Substituting the variable of years of schooling with variables of knowledge from the PIAAC scores barely has an influence on the estimated effect of work experience (columns 2-4). The gender and the nationality of the worker are still significant, but the effects on wages are reduced substantially (by half in the first case, by a third in the second). The knowledge of the individual has a significant positive effect on wages. On considering each area of knowledge separately, the estimations obtained suggest that each additional point in literacy increases the wage by 0.37%, much like the effect of an additional point in numeracy skills (0.38%). When considering the two types of knowledge simultaneously, both still have significant positive effects on wages, although those of numeracy skills are of greater magnitude. For each PIAAC point in numeracy there would be a 0.27% increase in salary, while each point for literacy would mean an extra 0.13%.

The significance of the years of study is robust to the consideration of the individuals' knowledge and that of knowledge is robust to the inclusion of the years of study, as indicated by the estimations that incorporate both dimensions simultaneously (columns 5-7). However, the estimated magnitude of all effects now turns out to be lower. The wage performance per year of schooling drops one point compared to the 7.1% previously estimated and is slightly above 6%. The drop in the effect of the knowledge variables is, in relative terms, even steeper and is reduced to less than half of the previously estimated effects. The effect for each point of literacy would be 0.13% and for numeracy 0.15%. On considering these two questions at the same time numeracy would maintain its effect, while literacy would no longer be significant.

Using the variable of years of education means considering that the performance of one year of education is always the same over the successive levels of education attained by the individuals. Each year of primary would give the same as each year of secondary or higher education. Inasmuch as the reality diverges from that hypothesis, the estimations will be conditioned by this circumstance.

We obtain the results of Table 3.5 by allowing the performance of education to vary according to the level of education instead of using the variable years of schooling and imposing a constant performance. These results confirm that the wages increase progressively along with educational levels. The effect of completing lower secondary education would not be significant compared to having primary education at most, but completing upper secondary education would mean, *ceteris paribus*, 27% higher wages, completing non-university higher education would mean 30%, and a university degree would correspond to a 67% higher wage.

Considering the individual PIAAC scores rather than the educational levels to estimate wage equations, we obtain the results in columns 2-4. The estimated effect of the other variables is maintained, although there is a significant decrease in the one corresponding to gender, especially once we include the PIAAC variable of numeracy, since it drops to less than half of that obtained when including the educational variables. The PIAAC scores have a significant and positive effect, its magnitude being very similar both for literacy and numeracy. For each additional PIAAC point wages would grow about 0.4 percent. When including the two variables at the same time (column 4), both are still significant, although it turns out to be more intense in the case of numeracy. Wages would grow by about 0.1% for each additional PIAAC point for literacy and around 0.3% for each PIAAC numeracy point. The aggregate effect of an extra point in every type of knowledge would stay between 0.3 and 0.4 percent.

These results confirm that knowledge is a very relevant determinant of wages, especially numeracy skills, which seem to be the most decisive in increasing worker productivity. However, it does not seem able to completely substitute the role of educational variables in explaining the behaviour of wages. In columns 5-7 both PIAAC scores and educational variables are included at the same time. Both have significant positive effects on wages. Wages increase along with the educational level whatever the skills level reflected by PIAAC, and they also grow with the PIAAC scores regardless of the level of education completed by the individual. The magnitude of the effects is, however, lower than when they were considered separately. The positive effects of further education after lower secondary education are reduced by between a fifth and a sixth. According to these estimations completing upper secondary education would mean, *ceteris paribus*, a 20% increase in salary, completing non-university higher education a 22% increase, and a university degree would correspond to a 56% higher wage. The effect of better PIAAC scores falls noticeably and is reduced to half the previous estimation. For each additional PIAAC point in numeracy wages would increase, but only around 0.16%.

Table 3.5. Wage regressions with levels of education as an explanatory variable. Dependent variable: logarithm of the wage per hour worked

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ref: Man	Woman	-0.1576 ***	-0.0713 ***	-0.0472 **	-0.0520 ***	-0.1407 ***	-0.1271 ***	-0.1269 ***
		(0.0186)	(0.0197)	(0.0194)	(0.0192)	(0.0187)	(0.0187)	(0.0186)
Ref: National	Foreigner	-0.1422 ***	-0.1040 ***	-0.0983 ***	-0.0919 ***	-0.1101 ***	-0.1011 ***	-0.1016 ***
		(0.0339)	(0.0329)	(0.0313)	(0.0317)	(0.0326)	(0.0317)	(0.0319)
	Exper.	0.0208 ***	0.0219 ***	0.0205 ***	0.0208 ***	0.0207 ***	0.0201 ***	0.0201 ***
		(0.0034)	(0.0037)	(0.0038)	(0.0038)	(0.0034)	(0.0034)	(0.0034)
	Exper.^{2}	-0.0002 ***	-0.0003 ***	-0.0002 **	-0.0002 **	-0.0002 ***	-0.0002 **	-0.0002 **
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Ref: Up to primary	Lower secondary	0.0481				0.0239	0.0135	0.0137
		(0.0310)				(0.0329)	(0.0335)	(0.0334)
	Upper secondary	0.2728 ***				0.2245 ***	0.2031 ***	0.2034 ***
		(0.0332)				(0.0353)	(0.0362)	(0.0361)
	Tertiary-type B	0.2998 ***				0.2485 ***	0.2262 ***	0.2265 ***
		(0.0338)				(0.0368)	(0.0381)	(0.0380)
	Tertiary-type A	0.6677 ***				0.5854 ***	0.5614 ***	0.5625 ***
		(0.0344)				(0.0399)	(0.0411)	(0.0411)
	Literacy score		0.0037 ***		0.0013 ***	0.0013 ***		-0.0001
			(0.0003)		(0.0005)	(0.0003)		(0.0004)
	Numeracy score			0.0038 ***	0.0027 ***		0.0015 ***	0.0016 ***
				(0.0003)	(0.0005)		(0.0003)	(0.0004)
	Constant	1.6981 ***	0.9737 ***	0.9790 ***	0.9069 ***	1.3975 ***	1.3453 ***	1.3512 ***
		(0.0384)	(0.0845)	(0.0815)	(0.0872)	(0.0766)	(0.0786)	(0.0806)
	N	2506	2507	2507	2507	2506	2506	2506
	R^2	0.3244	0.1862	0.1976	0.2011	0.3330	0.3382	0.3382
	F	106.48	72.98	76.55	63.72	96.75	97.64	87.19

***, **, *: Significant at 1%, 5% and 10% respectively. Standard errors in brackets, calculated using the Jackknife2 replication procedure for 80 replicated weights.
Source: PIAAC and authors' calculations.

We can try to show this effect in other terms tentatively and with caution. Assuming that the equivalence between a year of schooling and PIAAC scores is similar to that of PISA, a course would be roughly equivalent to 40 points. According to the estimates in column 7 of Table 3.4, one year of additional studies would imply, ceteris paribus, a wage higher by 6.1%. Moreover, 40 additional points in math PIAAC would mean, ceteris paribus, a 6% increase in wages[5]. Effective learning may therefore double the wage returns of a year of schooling.

The greatest effect of mathematics concerning reading comprehension is consistent with those obtained by analyzing the relationship between economic growth of countries and their levels of education and skills, Hanushek and Woessmann (2011). Moreover, in such studies on growth it is common that when the skill level is included as an explanatory variable the educational level variable ceases to be significant. In our case this does not happen, its effect is only reduced. Similar results are obtained in other papers that analyse the determinants of wages, as Denny et al. (2004) and Hanushek and Zang (2009). It is to be observed that the international analyses mentioned use homogeneous test scores especially designed for this case, while the differences between the educational systems can be very substantial across countries in terms of structure, content and degrees granted. That could affect the results in terms of the relative significance of the variable level of education compared to the variable of

[5] The difference between the numeracy score of Spain (246) and the best positioned countries such as Japan (288) and Finland (282) is around 40 points. Reaching those levels without changes in educational levels would increase wages by around 6% (column 7, Table 3.4). Doing it with increases in educational levels commensurate with the improvement of skills (column 3, Table 3.4) would increase wages by about 15%.

skills, measured more accurately. This problem should be much lower when considering the case of a single country.

The picture we get from the wages analysis is similar to that already mentioned regarding the other aspects of the individual's transition into the labour market that we discussed previously. First of all, education has significant and very substantial positive effects. Part of these are closely related to the amount of education, whose importance is maintained, though somewhat diminished, even taking into account the knowledge and literacy and numeracy skills of the individuals. The results in Villar (2013) using PIAAC data for Spain point to schooling as a key variable in order to improve numeracy proficiency in a similar way to what Desjardins (2003) obtained previously for reading comprehension. On the other hand, the effect of a certain amount of education seems to be conditioned by the quality of the training process itself. The greater the success in transforming the time spent in getting more knowledge and more developed skills, the greater is the productive capacity of the same period of schooling and, therefore, clearly the higher the wages. From an alternative perspective, the results also suggest that although a greater innate ability of the individual in itself has a positive effect, that effect is greatly increased if it is accompanied by a higher educational level. It is reasonable to consider that the successive levels of education, for example different university degrees, should contribute with useful knowledge and skills, general or specific, to the individual’s labour career beyond numeracy and reading comprehension.

EFFECTS OF THE IMPROVEMENT IN KNOWLEDGE: SOME SCENARIOS

The effects of educational levels and levels of skills and knowledge previously estimated individually have also implications for the aggregate behavior of the labour market and the economy as a whole. Next we propose an approach to estimating the effects that different improvements in the level of knowledge of the Spanish population would have at an aggregate level. The results of these simulations are an interesting reference point for assessing the potential importance of policies that could make an advance in this area.

The simulations are carried out under the assumption that after the improvements the previously estimated individual effects are maintained. The results must be taken with caution since their purpose is simply to provide an initial approximation of the potential gains. Thus, for example, the overall improvement of the levels of knowledge and skills of the Spanish population would mean a change in the relative supply of different types of workers that could reduce some of the wage benefits or the employment probability effects previously estimated. On the other hand, as suggested in Acemoglu (1998), it could provide a boost for technical progress increasing, *ceteris paribus*, the estimated effects in the long term. None of these possibilities has been taken into account in the simulations.

The scenarios considered correspond to changes that mean general improvements of varying degrees of intensity involving the movement of a certain part of the population from each

PIAAC performance level of numeracy competence to the next highest: from <1 to 1, from 1 to 2 from 2 to 3 and from 3 to 4. The results obtained for literacy scores would lead to similar conclusions.

Table 3.6 shows the estimated effects in terms of changes in the activity and unemployment rates, as well as in terms of the relative change in productivity. To do this we used the results of previous analyses of the determinants of wages, probability of participation and probability of employment. Two cases have been considered. The first corresponds to the estimated effects of PIAAC scores regardless of the educational level completed by individuals. The second case is obtained from the estimated effects of the PIAAC scores for given education levels that are assumed to be constant even though the population moves from some PIAAC levels to others.

Table 3.6. Aggregate effects estimated for different scenarios of improvement in the PIAAC scores

Moves from one level to the next:	Without considering the educational level			Given the educational level		
	Rate of activity	Rate of unemployment	Productivity	Rate of activity	Rate of unemployment	Productivity
1% of the population	0.19	-0.29	0.63	0.12	0.20	0.24
5% of the population	0.95	-1.47	3.17	0.59	1.00	1.20
15% of the population	2.85	-4.42	9.50	1.76	2.99	3.60

Results referring to changes in the numeracy scores. Rates of activity and unemployment variations in percentage points. Percentage variation of productivity in %.

The results of the first case show that general improvements in the levels of knowledge of the Spanish population would have positive aggregate effects, increasing the rates of activity and productivity and reducing the unemployment rate. The intensity of those estimated benefits depends on the magnitude of the improvement in knowledge. For very small improvements the effects are also modest. Thus, assuming that only 1% of the population moves up one PIAAC level, the change in activity rates and unemployment would be only two tenths of a point and improvement in productivity would be 0.6%. With more substantial changes the benefits would be more noticeable. Thus, if the change in level affected 15% of the population, the increase in the activity rate and the drop in the unemployment rate would comfortably exceed 2 percentage points, while productivity would increase by about 10%.

Behind these estimated results is the implicit assumption that educational levels would have changed together with the simulated improvements of the PIAAC scores. When that is not the case, using the estimated effects of the PIAAC scores conditioned to existing educational levels, we obtain scenarios with significantly more moderate benefits. For the assumed change of 15% of the population, productivity would improve considerably less, by 3.6%. The increase in the activity rate and the drop in the unemployment rate would be lower by more than one percentage point than those mentioned above.

The high rates of temporary employment in Spain make more difficult to achieve these positive scenarios. The results in Cabrales et al. (2013) indicate that receiving occupational training increases skills, although having temporary contracts reduces the probability of receiving such training. Moreover, Robles (2013) shows the significant and negative effect that the last reform of the Spanish educational system (LOGSE reform) had on numeracy skills. An improved performance will certainly require some changes in both the educational system and the regulation of the labor market in Spain.

CONCLUSIONS

Spain's participation in the PIAAC study on knowledge and skills of the adult population allows us to assess, with due caution, the economic effects of education in our country taking into account aspects related to the quality of education and not just the amount of education received or the number of years of schooling.

The results obtained show that the levels reached in literacy and numeracy skills significantly and positively influence the labour outcomes of the Spanish people, improving the transition into the labour market and promoting better careers, with less exposure to unemployment and characterized by higher wages.

This indicates that a mere quantitative increase of the educational system and its expansion including larger parts of population, will produce less satisfactory results for students and the whole of society unless it is accompanied by a determined effort to improve quality. In agreement with this result, the effects which can be attributed to completing successive levels of education are reduced noticeably when taking into account the PIAAC scores.

However, the PIAAC scores do not fully substitute the role of educational levels as a determinant of the employment situation of the individuals. Given certain levels of literacy and numeracy skills, a higher level of education means more participation in the labour market, less probability of being unemployed and higher wages. The effects associated with the numeracy skills are especially significant and positive compared with those related to literacy.

The simulations carried out show that policies which promote a better functioning of the education system, with better results in terms of knowledge and skills achieved by students, can have noticeable positive effects on activity and unemployment rates, as well as on labour productivity and ultimately, on per capita income and the living standards of the population.

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4. Education, labour market experience and cognitive skills: A first approximation to the PIAAC results

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4. EDUCATION, LABOUR MARKET EXPERIENCE AND COGNITIVE SKILLS: A FIRST APPROXIMATION TO THE PIAAC RESULTS[1]

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ABSTRACT

The productive specialization in low value added sectors and the high unemployment rate have raised concerns about the level of human capital of the Spanish population and the future employability of unemployed workers. This paper documents how human capital related to numeracy and literacy skills varies with work experience, according to the data obtained from the PIAAC study. These data show that the results of numeracy and literacy tests are higher among workers with higher levels of education, but that they only increase with the number of years worked for workers with primary education. However, wages increase with work experience for workers with higher education levels. Examining the detailed tasks content of the job positions, we find that among individuals with primary education the results of numeracy and literacy tests are higher for those who perform basic numeracy or literacy tasks at work - such as calculating percentages or reading emails, tasks which are performed by 20- 30% of them. On the other hand, among groups with a university degree, cognitive skills are higher for those workers who carry out advanced numeracy and

[1] This paper has been written as support material to the presentation report of the PIAAC study. We thank Luis Miguez Sanz, Francisco Garcia Crespo and Ismael Sanz their help with the database, and, especially, Inge Kukla for her excellent assistance in the preparation of this report. The opinions and analyses in this study are those of the authors and, therefore, do not necessarily coincide with those of the Bank of Spain or of the Eurosystem.

literacy tasks - preparation of graphs, regression analysis or composition of texts - as performed by over 60% of them. Moreover, for individuals with basic education, the correlation between the execution of basic tasks and cognitive skills does not vary much with job instability, though it decreases in the case of workers with a university degree performing advanced tasks at work. One interpretation of our results is that basic human capital, whose return is typically lower than that of specific human capital, is acquired either through the education system or by performing certain basic tasks at work. For the high education group, performing advanced tasks at work in a stable environment, is positive for human capital accumulation, while being in unstable environments or performing basic tasks can be detrimental.

INTRODUCTION

One of the best known results in Economics regards the importance of human capital. There is plenty of empirical evidence on the relationship between human capital and work performance. In this respect it is usually distinguished between human capital that is acquired in the formal education system and that obtained by learning through performing certain tasks at work, or by occupational training.[2] Since the seminal study of Mincer (1974), earnings equations that relate the individuals' work performance with their level of education and work experience are, without any doubt, one of the most widely used empirical instruments in Labour Economics and in Economics of Education, and as justification for the formulation of employment and educational policies. Similarly, it is also postulated that education and work experience increase the probability that workers are employed since, ultimately, this probability depends on the relationship between the wages offered to remunerate skills and the wage which the person is willing to work for.

However, earnings offered at a given point in time depends on factors other than the human capital acquired, such as, for example, the remuneration that the job market offers for a certain skill, which in turn is related to the demand for different skills, the way in which wages are determined (coverage and structure of collective negotiation, pay according to length of time in the job, etc.), and the individual reservation wage under which the worker is not willing to accept any job offer. Some of these factors imply that education or work experience is better remunerated even if there is not an increase of skills and productivity of an individual, derived from their human capital. For this reason, having standardized measures of cognitive skills allows researchers to better verify the relationship between educational level, work experience and human capital. Thanks to the availability of databases that combine the results of performing different tests of knowledge with training and labour characteristics, researchers have been able to investigate the relationship between education and experience and human capital, and their relevance as determinants of multiple socioeconomic results,

[2] See Rosen (1972)

such as wage levels and employment status. [3] Moreover, using standardized measures of cognitive skills has the advantage of them being observable for the entire population, while wages are only observed for the employed population, so that, in this case, significant sample selection makes statistical inference difficult.

In any case, discerning which is the cause of the association between work performance, on the one hand, human capital on the other, and education level and work experience, is not only of academic interest. The rationale for active job market policies focused on job training, and the design of programs through which these policies and other employment policies are carried out, has to take into account the extent to which formal education and work experience end up causing an increase in wages and the employability of workers.

The nature of the relationship between job performance (wages and employability), human capital and education and work experience is disputed due to a problem known as *omitted variables*. This means that while education and work experience increase worker's productivity and, therefore, end up leading to higher wages and a higher employment rate, they also may be a reflection of other unobserved individual characteristics that could be rewarded in the labour market with higher wages and employment rates.

In Labour Economics and Economics of Education, the empirical literature has addressed this issue by trying to isolate the causal impact of education and work experience through the use of advanced econometric techniques (instrumental variables, natural experiments, etc.) [4] Given the difficulties of identification in estimating wage/employment functions and the measurement of the relevant variables (work experience, cognitive skills, etc.) the results from this literature are not fully conclusive, although they suggest that education and work experience are determinant factors of improvements in cognitive skills and, consequently, of work performance, beyond their relationship with other unobserved individual characteristics (Card, 1994, Angrist and Krueger, 1991, Carneiro, Heckman and Vytlacil, 2010).

In Chapter 3, Hernández and Serrano (2013) examine the link between formal schooling, cognitive abilities and labor maket outcomes. Our aim in this paper is to contribute to the knowledge about how work experience is related to cognitive skills and work performance by using the information provided by the new database constructed from the PIAAC initiative of the OCDE, which contains measurements of numeracy and literacy skills resulting from a standardized exam, lasting about two hours and covering the entire working-age population. This provides very detailed information on the abilities of individuals, comparable both between individuals as well as, in the future, between the countries of the OCDE. [5] Secondly,

[3] See, for example, Heckman (1995), Murnane, Willet y Levy (1995) y Cunha y Heckman (2007).

[4] For an overview, see Card (1999)

[5] The target population of the survey is composed of individuals, not households, and sampling was carried out with the help of the National Institute of Statistics. The response rate for individuals has been around 50%, relatively low, although preliminary studies in the Ministry of Education do not suggest that the impact of this low response rate has affected the coverage of the sample. Finally, in the other countries, respondents were also examined on their IT abilities, but this module has not been implemented in Spain.

the survey collects detailed information on the contents of both the formal studies of the respondents, as well as the tasks performed at their last job.

The paper examines, firstly, the relationship between work experience and the standardized measurements of cognitive skills of the individuals in the PIAAC sample, distinguishing the effects of gender, educational levels and age.[6] One reason why we should expect differences in cognitive skills due to work experience refers to the erosion of skills during extended periods of unemployment or non-participation in the labour market.[7] Some studies examining this issue observe that the depreciation of human capital seems to depend on the duration of non-participation spells and not so much on the level of qualification prior to the period of unemployment. On the other hand, an active worker engaged in tasks in which the cognitive skills have to be used, not only does not experience that depreciation but she may also learn skills through learning on the job or through the dedication of their time to training activities.[8] The capacity of work experience to increase the cognitive skills of a person depends on multiple factors, some of these exogenous, such as genetics or the environment in which the individual lives, and some inherent to it, such as the cognitive skills acquired in formal studies or even other characteristics that make up what we could call non-cognitive skills.[9] It is for this reason that the analysis will take into account a significant number of factors that approximate individual differences in these dimensions, although since we are unable to control for all the unobserved differences we are not going to be able to establish any type of causal relationship. Thus, in short, our results should be understood as correlations from a first approximation to the data.

Secondly, the article examines the relationship between work experience and wages, also differentiating by gender, educational level and year of birth, to verify similarities with respect to the previously obtained relationship between experience and human capital. Preliminary results indicate that the effects of work experience on wages are different to those observed in relation to the accumulation of cognitive skills. For example, while work experience is associated with more developed cognitive skills in the case of workers with a lower educational level, the same does not happen with wages. Similarly, while work experience does not seem to be associated with more developed cognitive skills in the case of workers with higher educational levels, wages increase with work experience for this group of the population.

[6] From the beginning we assume that, for these purposes, there are no differences between unemployed workers who attend training courses and other unemployed or inactive workers. So, when we compare people of the same age and education with different levels of experience, we will be observing the difference in cognitive skills that have been used for more or less time (considering all possible alternatives - informal work, leisure and occupational, vocational or informal studies - equivalent to each other).

[7] See Jacobson, Lalonde and Sullivan (1993) and Bender, Schmieder and Von Wachter (2010).

[8] See Becker (1964) and Ben Porath (1967).

[9] By cognitive skills we mean an accumulation of factors among which stand out the perseverance to achieve a goal, ability of motivation to perform new tasks, self-esteem, self-control, patience, attitude towards risk and preference for leisure - see Cunha and Heckman (2007).

These results lead us to investigate some additional hypotheses. Taking advantage of the richness of the database, we go into more depth about how different types of work experience increase the cognitive skills of the individual. Firstly, given that jobs differ in the learning content they can provide, it is especially interesting to analyze what kind of tasks (basic or advanced) contribute better to on the job learning. We also look at the extent to which job instability (job rotation between different jobs) and the mismatch between formal education and tasks performed at work determine the association between work experience and cognitive skills. Regardless of the tasks performed on the job, in the Spanish labour market we see some quite short employment spells because of the high incidence of temporary contracts, and a remarkable degree of overqualification, mainly among workers in the youngest cohorts. In these cases, it could be expected that work experience does not generate any type of learning and, therefore, the association between work experience and cognitive skills would be reduced. Thus, it is important to establish the extent to which job instability and occupational mismatch are impediments to the accumulation of cognitive skills through on the job learning.

The paper is structured as follows. The second section documents the relationship between educational levels, work experience, and cognitive skills from the information provided by the PIAAC survey. To do this, we compare the cognitive abilities between people of the same sex age and educational level, but different with regards to the number of years worked throughout their working life, after trying to take away also all of the differences in cognitive skills that could come from other factors associated with family situation or non-cognitive individual characteristics. The third section documents the relationship between formal education, work experience, and wages in the same way as the second section, and we propose explanations for observed deviations from the results obtained regarding cognitive skills. In the fourth section we try to find out if, for the same number of years worked throughout the working life, the tasks performed in the last job position affect cognitive skills. To that aim, we analyze whether different types of job experiences biased towards literacy or numeracy tasks affect cognitive skills as measured by the PIAAC exam, and whether job instability and overqualification have effects on these skills. Finally, the last section contains some comments on the interpretation of the results and how they can be useful for the design of educational and job training policies.

WORK EXPERIENCE AND COGNITIVE SKILLS

The PIAAC survey has been designed to measure cognitive skills by means of numeracy and literacy tests. Work experience is obtained by the individuals' responses to the question: *"In total, approximately how many years have you been in paid work? Include only those years in* *which you worked for six months or more, full time or part time?"*[10]. A first observation of both variables (see Figures 1 and 2) leads to the following conclusions:

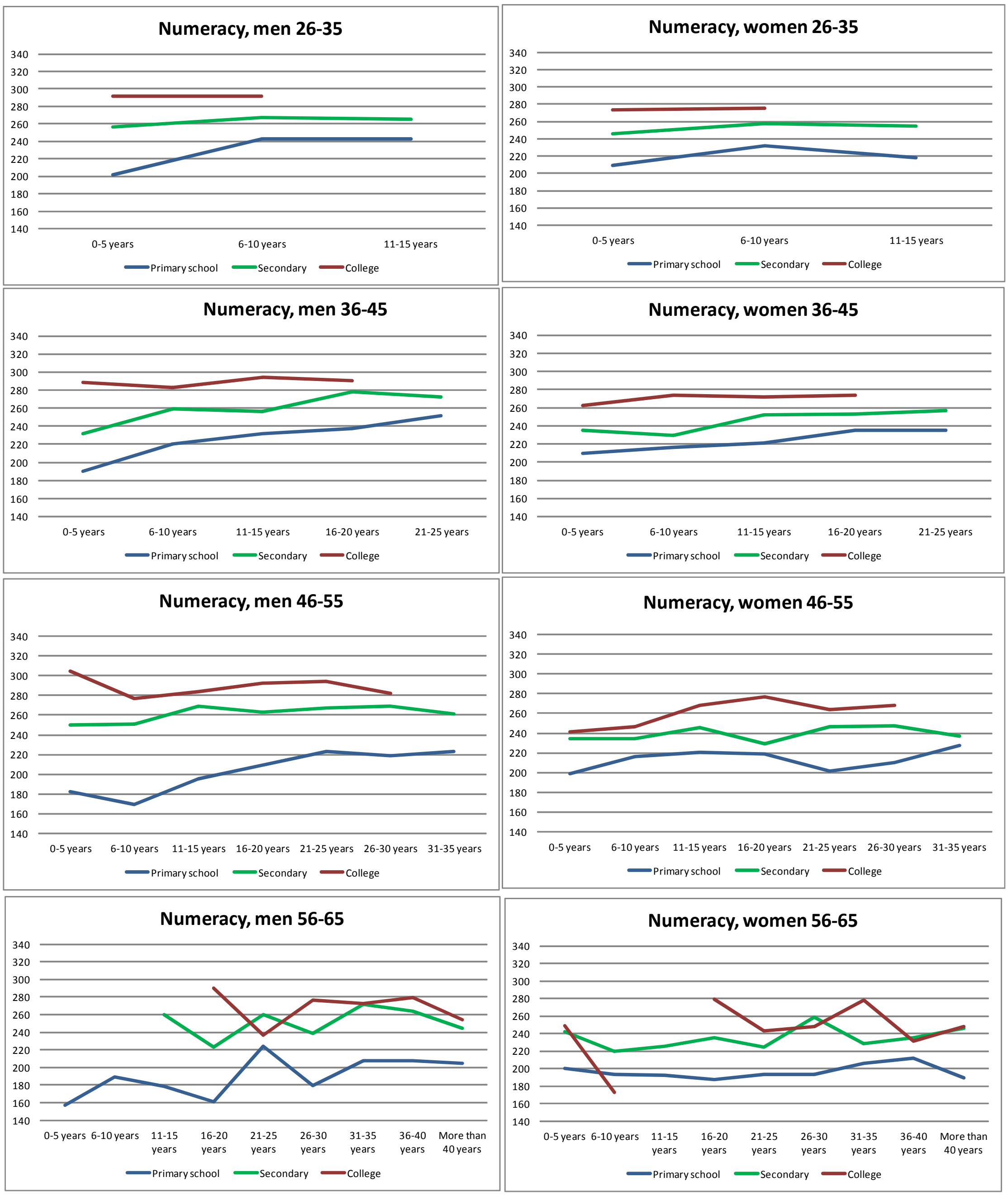
Keeping constant labour market experience and age, defined in 10 years' ranges, the higher the educational level is, the higher the results of the numeracy and literacy tests are. Men with intermediate education (intermediate Professional Training -FP in Spanish- or Bachellor degrees) obtained results in the numeracy test which were between 20 and 40 points higher than those with primary education. These differences are similar for women, although, in their case, while men with university education (or higher FP) got 20 points more than those with intermediate education in the numeracy test, the difference in performance of both educational groups for women was only 10 points -for males and women with 11 to 15 years of labour market experience-. The differences in the numeracy test scores by education groups are more acute in the case of the cohort of men born before 1965, while in the case of women these differences between education levels are rather similar between the different age cohorts.

Women with low educational levels at the beginning of their working lives got higher scores than men, while women with high educational levels, at the same moment of their working career ,have lower scores than males of the same age cohort and labour market experience. Women with high educational levels, in any of the stages of their working lives, have worse test results than males with similar characteristics.

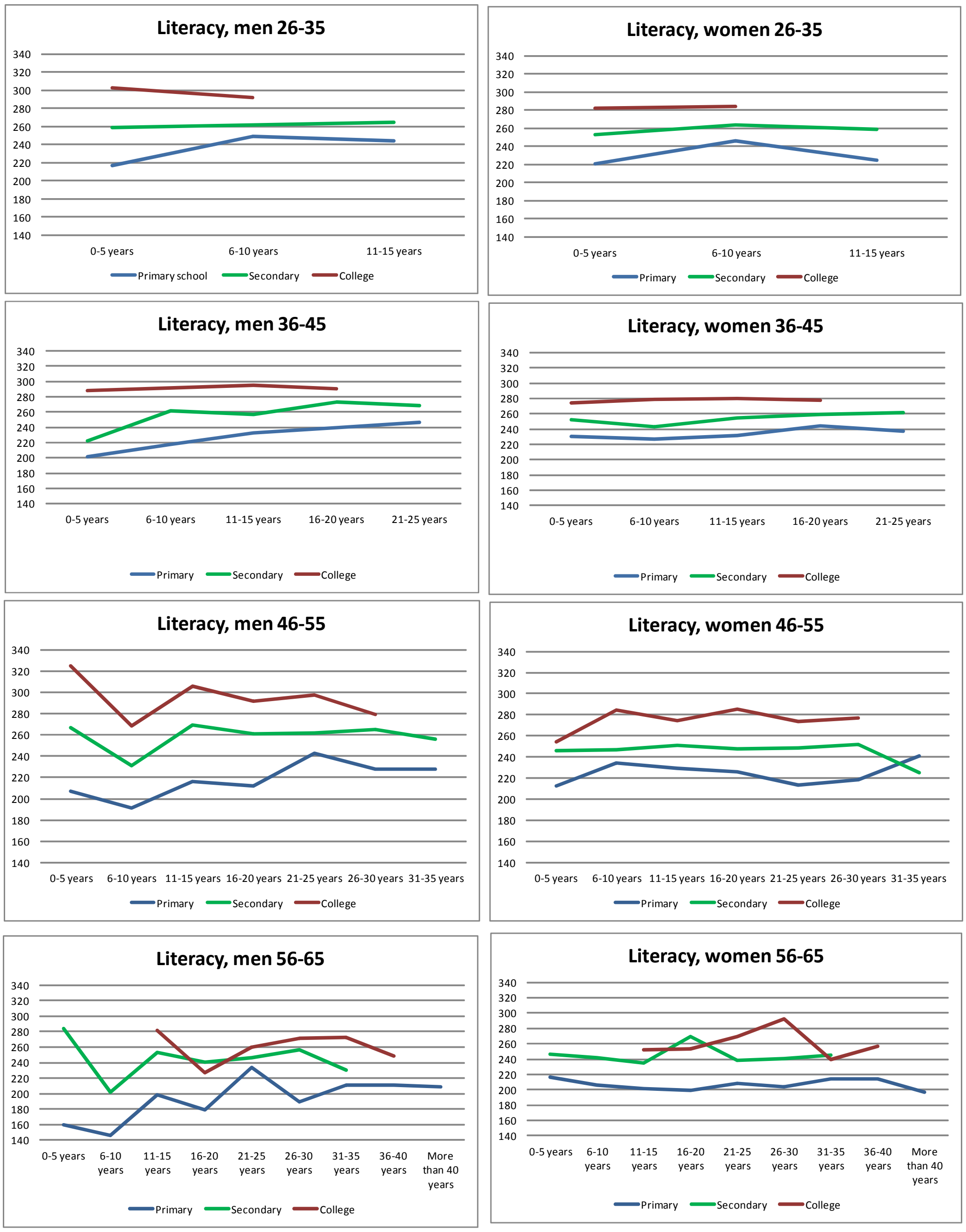
Secondly, the tests results increase with labour market experience (defined in 5 years' ranges), mainly for individuals (males and women) with low educational levels. This positive gradient is more pronounced for males than for women and, surprisingly, is not observed in any case for individuals with medium-high education levels. The results for males over 56 years and for women older than 46 years are more volatile, something which highlights the convenience of performing the analysis by distinguishing between different age cohorts. Thus, from now on we shall report results for two population groups, a more homogeneous one which includes 25 to 45 years old, and another which also includes 46 to 65 years old. It should be noted, however, that in the second sample it is more difficult to separate the effects of labour market experience from those associated with age.

[10] In this version of the study, we use only one of the ten different imputations of the score for each test for each individual, so that the results are preliminary. A sample of 4,374 individuals between 25 and 65 years old is selected. The lower age limit increases the probability of having completed the period of formal education and avoids the problems associated with greater practice in the exam preparation of those individuals who are doing university studies. On the other hand, retired individuals are excluded, given the interest in the working age population. Finally, educational groups are grouped into three levels: primary education or less, baccalaureate studies as well as modules of Professional Training (FP) that, according to the ISCED classification, do not constitute university education, and any type of university education, including the higher module of Professional Training (FP) in each educational system.

Graph 4.1: The relationship between numeracy test and years of work experience by gender, year of birth and educational level



Graph 4.2: Literacy test by gender, year of birth and educational level



Each panel of Graph 4.1 (and 4.2) shows the average score of the cohort in the numeracy (literacy) test by labour market experience . The years of experience prior to 16 years old are not counted, and students are excluded. We consider three educational groups: university or equivalent (college), secondary and primary school).

To go into these descriptive results in more depth we carry out multiple regression analysis that take into account other determinants of cognitive skills besides age, gender, educational levels and labour market experience, such as nationality and region of residence, family situation, state of health, and attitudes towards learning. To allow the effect of experience on the test scores to vary over the life span, we include a function - a second-order polynomial- of labour market experience. From the results of these regressions (see Tables 4.1 and 4.1b) it is worth highlighting the following observations:

For males of younger cohorts (25 to 45 years old) and low educational levels, the first ten years of labour market experience is associated with an increase in the results of the numeracy and literacy tests of about 20 points and 10 points, respectively (being the standard deviation of the marginal distribution of the scores of 25 points). For university graduates, the corresponding increases is 7 and 0 points, respectively. This suggest some substitution of education and labour market experience in the accumulation of cognitive skills. Given that in both tests the direct effect of education levels is around 60 points for men with university degrees over those with primary education, the contribution of labour market experience to explaining the variance of the numeracy tests results is three times lower than the effect of education, and non-existent in the case of the literacy test.

For women of the younger cohorts (25 to 45 years old) with low education levels, the first ten years of experience is associated with an increase of the numeracy test results of 14 points, and barely 2 points in the literacy test. For women with university studies in this same age cohort the corresponding increases are 10 and less than 2 points, respectively. In this case, the direct effect of having university studies is around 47 and 41 points, respectively, somewhat lower than in the case of men.

When the older cohorts are included in the sample (46-65 years old), results aremore volatile so that, in the case of males, the first ten years of work experience is associated with an increase of the results of the numeracy test of 14 points, and 6 points in the literacy test. In this case, the effect is independent of the education level, suggesting that the fact that labour market experience has no effect on the test results of males with higher education levels is mainly due especially to the younger cohorts. In this case, the direct effect of having university studies compared to a person who has not finished non-compulsory intermediate studies is around 50 points in both tests, so that what the contribution of labour market experience to explaining the variance is four to five times lower than education for the numeracy test and nearly 10 times lower for the literacy test.

In the case of women, the inclusion of the older cohorts in the sample indicates that the first ten years of labour market work experience is associated with increases of the numeracy and literacy tests results of about 6 points and barely 1 point, respectively, increases that are rather similar for all educational levels. In this case, the direct effect of having university studies compared to women who have not completed the non-compulsory intermediate studies is around 40 points in both tests, so that the contribution of labour market experience to explaining the variance is seven times lower than education for the numeracy test and about 40 times lower for the literacy test.

Regarding other determinants, the results are in line with what it could be expected. Firstly, foreigners have worse results, which can be attributed, in some cases, to the language barrier and, in others, to a different socio-economic background. Regional differences (not reported in the tables) are difficult to interpret, since the sample design does not ensure that the sample is representative of the region analyzed.[11] Better results in the tests tend to be associated with the existence of a relationship with a partner (especially visible in the case of the numeracy test for men and in the literacy test for women). The educational level of the mother also has a noticeable effect on cognitive skills, measured by the test results, which turn out to be of a similar magnitude to that of the negative attitude towards learning.

[11] Keeping all other variables constant, the model of the first column of Table 1 suggests a difference of 32 points between an employed woman of between 26 and 45 years old with basic education in Castilla y Leon, the region with the best results, and Murcia, the region with the worst score for this group. Respondents in Castilla y León, La Rioja and Valencia scored more than 10 points above the average in the numeracy test, while respondents in Murcia got 12 points less than the average. In the case of males, respondents in Aragon, the Balearic Islands, the Canary Islands and the Basque Country got results that were 10 points below the average. The regional variation of the literacy test results is similar.

Table 4.1a. OLS regresión of test scores on experience and socio-demografic variables. Ages 25-45

	Males		Females	
	(1)	(2)	(3)	(4)
COVARIATES	Numeracy	Literacy	Numeracy	Literacy
Labour market experience				
Experience	1.993**	1.022	1.413*	0.188
	(0.876)	(0.850)	(0.792)	(0.741)
Experience squared	-0.0393	-0.0227	-0.0357	-0.00303
	(0.0264)	(0.0262)	(0.0307)	(0.0277)
Experience*Medium schooling	-0.286	-0.00611	-0.165	-0.00861
	(0.465)	(0.449)	(0.575)	(0.511)
Experience*College	-1.286***	-1.386***	-0.379	-0.0750
	(0.410)	(0.407)	(0.435)	(0.429)
Schooling				
Medium schooling	29.17***	22.33***	24.99***	20.67***
	(7.191)	(7.071)	(6.934)	(6.162)
College or more	60.42***	60.43***	47.30***	41.24***
	(6.468)	(6.364)	(5.419)	(5.257)
Socio-demographics				
Migrant	-32.91***	-31.91***	-24.73***	-24.84***
	(3.852)	(3.833)	(3.501)	(3.232)
Married	6.535**	2.702	4.097	4.557*
	(2.600)	(2.525)	(2.738)	(2.522)
Not employed	-14.95***	-12.66***	-1.527	-0.756
	(2.957)	(2.925)	(2.633)	(2.488)
Parental background				
Mother has medium schooling at least	14.41***	10.35***	12.58***	12.69***
	(3.475)	(3.450)	(3.203)	(3.147)
Mother schooling non reported	-19.39	-11.91	-3.663	-2.497
	(13.30)	(12.96)	(8.085)	(7.088)
Mother employed when respondent was 16	-0.813	0.00749	2.137	2.657
	(2.484)	(2.427)	(2.414)	(2.353)
Mother deceased by the age of 16 of the respondent	14.47	20.46**	-30.56***	-10.40
	(10.60)	-9761	(10.97)	(9.882)
Non-cognitive characteristics				
Not interested in learning new things	-14.90***	-11.78***	-7.779**	-8.119**
	(3.650)	(3.549)	(3.629)	(3.397)
Very interested in learning new things	-1.747	0.392	1.938	0.302
	(2.390)	(2.413)	(2.437)	(2.340)
Good health status	0.541	2022	-0.382	3.928*
	(2.432)	(2.404)	(2.468)	(2.349)
Poor health status	-5409	-7.988**	-9.734***	-9.482***
	(4.068)	(3.923)	(3.534)	(3.439)
Other				
Region dummies	Yes	Yes	Yes	Yes
Cohort 26-35 indicators	Yes	Yes	Yes	Yes
Constant	226.8***	240.2***	217.2***	231.0***
	(9.720)	(9.229)	(7.108)	(6.693)
Number of observations	1,223	1,223	1,216	1,216
R-squared	0.398	0.382	0.350	0.338

Heteroscedasticity-adjusted standard errors in parentheses (Huber -White adjustment)
*** p<0.01, ** p<0.05, * p<0.1
Omitted group: Single native with primary schooling , 36-45 years, employed, interested in learnings new things, with fair health and whose mother had primary schooling and was not working when the respondent was 16.

Table 4.1b. OLS regresión of test scores on experience and socio-demografic variables. Ages 25-65

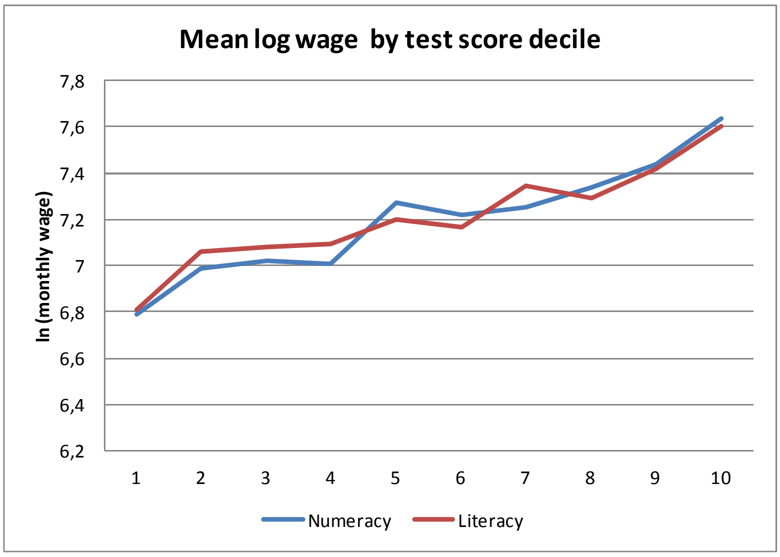
	Hombres		Mujeres	
	(1)	(2)	(3)	(4)
COVARIATES	Numérico	Lectura	Numérico	Lectura
Labour market experience				
Experience	1.365***	0.644	0.624*	0.0965
	(0.446)	(0.430)	(0.350)	(0.334)
Experience squared	-0.0261***	-0.0162*	-0.0104	-0.00425
	(0.00889)	(0.00866)	(0.00821)	(0.00808)
Experience*Medium schooling	0.351*	0.202	0.231	0.190
	(0.206)	(0.204)	(0.228)	(0.213)
Experience*College	-0.0135	-0.268	-0.0559	0.173
	(0.193)	(0.190)	(0.209)	(0.212)
Schooling				
Medium schooling	26.60***	22.37***	20.82***	19.03***
	(4.842)	(4.810)	(4.380)	(4.017)
College or more	50.43***	51.03***	43.22***	37.99***
	(4.460)	(4.411)	(3.854)	(3.808)
Socio-demographics				
Migrant	-31.98***	-30.79***	-25.43***	-25.84***
	(3.389)	(3.346)	(3.006)	(2.820)
Married	6.847***	1.583	5.843***	5.586***
	(2.234)	(2.143)	(2.105)	(1.953)
Not employed	-15.73***	-13.96***	-1.254	-0.384
	(2.243)	(2.183)	(1.984)	(1.915)
Parental background				
Mother has medium schooling at least	13.56***	11.19***	13.48***	13.34***
	(2.944)	(2.923)	(2.694)	(2.618)
Mother schooling non reported	-27.78***	-14.64*	-8.915	-9.491*
	(9.037)	(8.579)	(5.913)	(5.052)
Mother employed when respondent was 16	-2.250	-1.862	0.655	0.861
	(2.061)	(1.969)	(1.916)	(1.861)
Mother deceased by the age of 16 of the respondent	-2.335	8.742	-18.13***	-3.296
	(7.748)	(6.251)	(6.677)	(6.649)
Non-cognitive characteristics				
Not interested in learning new things	-16.65***	-12.67***	-10.10***	-8.665***
	(2.604)	(2.467)	(2.572)	(2.487)
Very interested in learning new things	-1.232	0.633	3.302*	2.151
	(1.974)	(1.947)	(1.937)	(1.865)
Good health status	-0.347	1.540	1.001	4.034**
	(2.027)	(1.988)	(1.951)	(1.885)
Poor health status	-10.98***	-11.98***	-11.99***	-10.67***
	(2.614)	(2.500)	(2.387)	(2.320)
Other				
Region dummies	Yes	Yes	Yes	Yes
Cohort dummies	Yes	Yes	Yes	Yes
Constant	236.0***	244.2***	194.3***	209.3***
R-squared	(5.893)	(5.648)	(5.402)	(4.988)
Number of observations	2,134	2,134	2,187	2,187
R-squared	0.443	0.419	0.380	0.363

Heteroscedasticity-adjusted standard errors in parentheses (Huber -White adjustment)
*** p<0.01, ** p<0.05, * p<0.1
Omitted group: See Table 1

LABOUR MARKET EXPERIENCE AND WAGES

Before going on to investigate the reasons why the effect of labour market experience on cognitive skills is different according to gender and educational levels, it is worth analyzing the degree of association between declared wages and cognitive skills, as measured by the tests in the PIAAC sample. Only to the extent that both variables are correlated some conclusions about the importance of cognitive skills for job performance can de drawn. As shown in Graph 3, which relates the results of numeracy and literacy tests to wage earnings in each decile of the distribution of this variable, this statistical association exists and is particularly pronounced for the higher deciles of the wage distribution, which suggests that cognitive skills measured by the tests are relevant to job performance, especially so for the most educated, which possibly indicates that cognitive skills acquired by the more educated are better rewarded than those acquired by workers with low educational levels.

Graph 4.3: Wage earnings and cognitive skills



Apart from the effect that labour market experience can have on cognitive skills and, consequently, on the productivity of workers and the extent to which that increased productivity is reflected in a higher wage, there are other reasons why labour market experience may affect wages that have to do the influence of labour market institutions on wage determination. For example, if labour market experience has been acquired at the same workplace, and tenure at the firm is rewarded, either because it is imposed by wage negotiation, or specific tasks are learnt, which do not increase cognitive skills but nevertheless are are valuable for the firm, or because there are implicit contracts between firms and workers which lead to wage increases according to tenure as a way of providing incentives for effort (efficiency wages, etc.), we will observe a relationship between labour market experience and wages beyond that the relationship between cognitive skills and wages. In this regard, less turbulent careers, regardless of skills accumulated at the workplace, provide higher wages. In a similar vein, the existence of a minimum wage and collective bargaining agreements may impose floors and ceilings regardless of individual productivity.

One way to determine to what extent these other considerations are relevant in the case of the Spanish labour market is to estimate wage equations with specifications similar to those estimated in Tables 4.1a and 4.1b to document the determinants of the test results. The main conclusions from this estimation (see Tables 4.2a and 4.2b) are somehow different to those from the estimation of the determinants of the results of the tests, for example:

In the case of the younger cohorts of men (25 to 45 years old), the first ten years of experience are associated with an increase in wages of less educated individuals of 22%, while for those with university studies the increase is 37%. In this case, and in contrast with the results of the numeracy test, a certain complementarity between the labour market experience and education level *is* observed. The direct effect of having university education on wages is 21% over not having completed non-compulsory intermediate studies. Assuming that university graduates have had eight years more of education than those with basic studies, an additional year of labour market experience of the most educated workers contributes to explaining the variance of wages 38% more than one year of education (1.38 is the ratio between 37*8/10 and 21). For the less educated workers the contribution of one year of labour market experience is equivalent to one year of education.

For women of the younger cohorts (25 to 45 years old), the first ten years of labour market experience increases the wage for those with low education level by a sizeable 52%, and by 63% for those who have completed university studies. In this case, the direct effect of having university studies is greater than that of males (37% compared to those who have not completed their non-compulsory intermediate studies), so that what an extra year of labour market experience contributes to explaining the variance is 80% of the contribution of an additional year of education (0.8 is the ratio between 0.63*8/10 and 0.37).

When taking into account all of the age cohorts, in the case of males, the first ten years of labour market experience are associated with a wage increase of 1.6% per year on average, for those with low educational levels, and 2.4% for university graduates. In this case the direct effect of having university studies stands at 32% over not having completed non-compulsory intermediate studies, so that what an additional year of labour market experience contributes to explaining the variance around 60% of the contribution of an additional year of education.[12]

For women, the first ten years of work experience increase the wage of those with low educational levels by 3% per year on average and 4.5% for the university graduates. In this case the direct effect of having university on wages is about 36% over not having completed non-compulsory intermediate studies, so that what an additional year of work experience contributes to explaining the variance is similar to that of an additional year of education for the high edecaution group, and 75% for the lower education group.

[12] The fact that the wage impact of having university studies is greater when all age cohorts are included is consistent with the results of other studies that have documented a decrease in wage returns to education in Spain in recent years, especially among males (see Izquierdo and Lacuesta, 2012, and de la Fuente and Jimeno, 2010).

Regarding the other explanatory variables, keeping age, labour market experience, and education levels constant, wages are lower among foreigners - between 20 and 30 percentage points, and among women with worse level of health - around 10 percentage points.

From the conclusions that can be drawn from the comparison between the determinants of cognitive skills and wage earnings, it is worth highlighting the different impact of labour market experience in the case of individuals with low educational levels (positive on cognitive skills, and nil on wage earnings) weith respect to the case of workers who have completed university studies (no effect on cognitive skills, positive and greater than that observed for those with lower educational level on wage earnings). As we have noted previously this may be because the labour market values certain knowledge differently throughout the cognitive dimension. In particular it could be that the most advanced cognitive skills are valued more intensely in the market. It could also be that the process of wage determination takes into account job tenure, and it is this variable and not labour market experience that has more influence on wages. In fact, when time spent in the firm is included –under a linear and a quadratic terms-, we see that this coefficient of tenure is at least as important as that of labour market experience, and that the latter becomes not statistically insignificant.[13] In the next section we try to provide some results on the process of skills training based on the type of tasks performed at work, the match between these tasks and the worker's educational level, and the extent to which labour market experience has been accumulated over long periods of time working in the same job, instead of by a succession of many short employment spells at different jobs, that can help to clarify these issues.

[13] The economic literature has emphasized the inherent difficulties in interpreting the returns to job tenure. Wage increases associated with higher levels of tenure may indicate the returns to specific learning in the firm, the return to a better match between worker and firm or it may simply be the result of wage renegotiations after receiving better offers in other firms. Distinguishing between these factors, or others, is not trivial even when longitudinal samples are available (see the discussion in Altonji and Shakotko, 1987, Topel 1991 or Buchinsky et al., 2010)

Table 4.2a. OLS regression of gross log monthly earnings on experience and socio-demografic variables and non-cognitive indicators. Ages 25-45

COVARIATES	Males (1) ln(wage)	Females (2) ln(wage)
Labour market experience		
Experience	0.00362	0.0652***
	(0.0146)	(0.0177)
Experience squared	6.69e-05	-0.00231***
	(0.000465)	(0.000572)
Experience*Medium schooling	0.0146	0.0200**
	(0.00944)	(0.00917)
Experience*College	0.0164**	0.0120
	(0.00690)	(0.00895)
Schooling		
Medium schooling	-0.0113	-0.118
	(0.153)	(0.144)
College or more	0.209**	0.368***
	(0.106)	(0.124)
Socio-demographics		
Migrant	-0.313***	-0.186***
	(0.0622)	(0.0684)
Married	0.215***	-0.0440
	(0.0427)	(0.0528)
Parental background		
Mother has medium schooling at least	0.149**	0.0714
	(0.0747)	(0.0564)
Mother schooling non reported	-0.365***	-0.142
	(0.118)	(0.187)
Mother employed when respondent was 16	-0.0723	0.0687
	(0.0456)	(0.0454)
Mother deceased by the age of 16 of the respondent	0.172	-0.237
	(0.107)	(0.166)
Non-cognitive characteristics		
Not interested in learning new things	-0.0432	-0.0834
	(0.0516)	(0.0615)
Very interested in learning new things	-0.00148	0.0445
	(0.0405)	(0.0499)
Good health status	0.0424	0.108**
	(0.0375)	(0.0482)
Poor health status	-0.0711	-0.0414
	(0.0710)	(0.0791)
Other		
Region dummies	Yes	Yes
Cohort 26-35	Yes	Yes
Constant	7.139***	6.548***
	(0.138)	(0.154)
Observations	786	689
R-squared	0.260	0.282

Heteroscedasticity-adjusted standard errors in parentheses (Huber -White adjustment)
*** p<0.01, ** p<0.05, * p<0.1 See notes to Table 1.

Table 4.2b. OLS regression of gross log monthly earnings on experience and socio-demografic variables and non-cognitive indicators. Ages 25-65

VARIABLES	Males (1) ln(wage)	Females (2) ln(wage)
Experiencia		
Experience	0.0185**	0.052
	(0.00900)	(0.020)**
Experience squared	-0.000155	-0.0025
	(0.000195)	(0.00106)
Experience, cubic	--	0.0000415
		(0.0000167)
Experience*Medium schooling	0.00227	0.0156***
	(0.00707)	(0.00558)
Experience*College	0.00771*	0.0176***
	(0.00406)	(0.00472)
Schooling		
Medium schooling	0.153	-0.069
	(0.132)	(0.109)
College or more	0.316***	0.335***
	(0.0880)	(0.0886)
Socio-demographic variables		
Migrant	-0.252***	-0.196***
	(0.0557)	(0.0574)
Married	0.185***	0.0137
	(0.0395)	(0.0407)
Parental background		
Mother has medium schooling at least	0.0890	0.0973*
	(0.0822)	(0.0497)
Mother schooling non reported	-0.170	0.0230
	(0.107)	(0.114)
Madre con empleo a los 16 años	-0.0773*	0.0018
	(0.0398)	(0.0397)
Mother employed when respondent was 16	0.00245	-0.164
	(0.0909)	(0.090)*
Non-cognitive characteristics		
Not interested in learning new things	-0.0746	0.0316
	(0.0542)	(0.0483)
Very interested in learning new things	0.0244	0.0349
	(0.0361)	(0.0397)
Good health status	-0.0186	0.0824**
	(0.0386)	(0.0387)
Poor health status	-0.107**	-0.0600
	(0.0503)	(0.0539)
Other		
Region dummies	Yes	Yes
Cohort dummies	Yes	Yes
Constant	6.787***	6.741***
	(0.140)	(0.110)
Observaciones	1,188	1,089
R-cuadrado	0.217	0.319

Heteroscedasticity-adjusted standard errors in parentheses (Huber -White adjustment)
*** p<0.01, ** p<0.05, * p<0.1 See notes to Table 1b.

JOB TASKS, JOB STABILITY AND COGNITIVE SKILLS

In order to document the importance that the tasks performed at work have on cognitive skills we perform a regression analysis in which the results of the numeracy and literacy tests are thought to depend, besides all of the labour, educational and socio-economic factors considered above, on the type of tasks performed at the last job - the current job for employed workers and the last one for the unemployed - which the PIAAC survey provides information about. We group the tasks performed at work into two categories - basic and advanced- depending on the answers to questions regarding the intensity of the use of numeracy-literacy faculties required to carry out the last job tasks. Specifically the variable to consider (which takes 0/1 values) is whether respondents perform the following tasks at work at least once a month: i) basic (doing budgets, using a calculator, reading bills, using fractions, reading charts, reading guides, reading emails, reading manuals, writing emails, writing reports, reading articles), and ii) advanced (preparing graphs, using algebra, reading academic journals, reading books, writing papers). The primary objective of this analysis is to observe the impact of different tasks on cognitive skills. For more precise estimation, all the age cohorts of women and males are included in the sample. [14]

While it might seem that the above classification of tasks is arbitrary, the proportion of individuals of different educational levels who claim to perform them turns out to be consistent with prior expectations (see Tables 4.3a and 4.3b). Thus, the proportion of males who claim not to do any of these tasks or to perform at most basic tasks in their job is about 80% for those with low educational levels, and about 30% for those who have completed university studies. Regarding advanced tasks, the same proportions are about 16% and 68%, respectively. For women, the percentages of those who claim to perform none of these tasks or basic tasks at most are higher for all education groups, with smaller proportions of those claiming to perform advanced tasks, something which suggests, among other things, that the degree of the job mismatch of women workers with university studies is greater than that registered among males. With respect to individuals with low educational levels, the type of basic tasks that they claim to perform most frequently are the use of fractions, of the calculator, and the preparation of budgets. Meanwhile, among individuals with high educational levels the advanced tasks they claim to perform most frequently are the preparation of graphs, the use of algebra, and reading books and academic journals.

[14] A statistical test regarding the equality of coefficients, for males and women, of each of the tasks was carried out in linear regressions of the numeracy test results. The zero hypothesis of equality of coefficients between the two groups of population is not rejected - the p-value is below 20%. The results of a similar test for the literacy exam are very similar.

Table 4.3a. Percentage of workers performing at least once a month the task in the row –by schooling level

VARIABLES	Males Primary	Males Medium schooling	Males College	Females Primary	Females Medium schooling	Females College
Numeric tasks						
Basic						
Elaborating a budget	26,1%	43,4%	54,9%	17,2%	35,6%	43,2%
Using a calculator	23,7%	45,3%	65,2%	10,7%	31,8%	49,8%
Reading bills	22,0%	37,3%	50,6%	12,3%	33,7%	39,4%
Computing fractions	31,4%	51,5%	71,2%	17,6%	43,1%	59,6%
Reading diageams	20,8%	43,2%	68,8%	4,4%	15,1%	40,1%
Advanced						
Elaborating graphs	10,0%	31,0%	62,0%	0,3%	12,9%	44,4%
Algebra or regression analysis	9,6%	25,4%	51,7%	10,7%	31,8%	49,8%
Reading/Writing tasks						
Basic						
Reading guides	35,3%	61,7%	80,1%	18,2%	46,6%	67,3%
Reading electronic mail	27,1%	56,4%	79,7%	13,6%	47,2%	71,1%
Reading handbooks	31,4%	59,1%	78,6%	14,4%	40,6%	66,6%
Writing mails	23,7%	53,0%	78,3%	12,2%	44,7%	68,7%
Writing reports	20,7%	46,5%	70,8%	9,0%	29,5%	60,0%
Reading articles	19,0%	45,6%	68,4%	12,4%	31,5%	63,1%
Advanced						
Reading academic journals	14,9%	38,7%	65,0%	8,7%	24,8%	57,9%
Reading books	7,8%	18,0%	45,6%	5,5%	12,7%	41,2%
Writing books	0,5%	4,6%	16,9%	0,6%	2,6%	13,1%

Source: PIACC sample of individuals with some work experience.

Table 4.3b. Percentage of workers performing at least once a month the task in the row –by schooling level

	Males			Females		
VARIABLES	Primary	Medium schooling	College	Primary	Medium schooling	College
Numeric tasks						
None	53%	31%	14%	71%	46%	26%
Basic at most	31%	29%	18%	22%	36%	22%
Advanced	16%	40%	68%	6%	18%	53%
Reading or writing						
None	49%	26%	11%	65%	34%	18%
Basic at most	32%	32%	20%	21%	37%	19%
Advanced	19%	43%	69%	14%	29%	63%

Source: PIAAC

As shown in Table 4.4, the type of tasks performed in the last job has a positive effect on the results of numeracy and literacy tests, although it is heterogeneous and depends on the type of task and educational levels. Among individuals with basic education, those who perform basic math tasks at work - using a calculator, calculating fractions, and percentages– obtain 15 points more in the numeracy test than those who do not perform them -even within the same age cohort and the same work experience-. Among individuals with basic education, keeping the experience and age constant, those that perform advanced tasks -preparation of graphs, simple or complex algebra, or regression analysis – obtain 10 extra points on the numeracy test. For individuals who have completed university studies the same impact of the basic tasks has a negligible size and the impact of advanced tasks is about 20 points.

The heterogeneity in the relationship between tasks and test results shown in Table 4.4 is consistent with previous evidence about the way in which human capital is acquired in the job. The acquisition of cognitive skills throughout the working life can be understood as a series of investments made in the education system - acquiring skills in a formal way-; throughout the working life -acquiring skills according to tasks in the workplace-; or finally in other aspects of life -through interaction with family or friends-. Heckman (2013) shows that the different ways to acquire cognitive skills are complementary to each other at certain times of life -for example, the learning of certain tasks in the labour market would further increase the cognitive skills of individuals with a previous higher educational level- while, at the beginning of the working life, alternative ways of acquiring skills could be substitutes –for instance, cognitive skills could be acquired interchangeably at work or by formal education-.

In effect, one possible interpretation of Table 4.4 is that the cognitive skills that can be acquired by performing basic numeracy tasks - calculating percentages- can be learnt both in the education system and in the labour market, both alternatives being substitutes for one another. In fact, the basic tasks contribute 15 points to the numeracy test results of respondents with primary education, but only contribute 3 points to the cognitive knowledge of individuals with a Bachellor degree, Professional Training or University studies, who supposedly have already developed these skills in formal education.In contrast, individuals with university studies would increase their numeracy skills especially when performing advanced math tasks. For example, the routine performance of regression analysis or algebra would increase the numeracy abilities of individuals who previously understood the formal rudiments of statistics or mathematics, but would increase those of individuals with basic education to a lesser extent, since they have acquired that knowledge in a less systematic way over their working life.

Table 4.4. OLS regression of test scores on tasks on the job

VARIABLES	(1) Numeracy	(2) Literacy
Job involves any basic numeracy/literacy task	14.95***	13.84***
	(2.401)	(2.258)
Job involves any basic numeracy/literacy task * Medium schooling	-11.23***	-9.681**
	(3.914)	(3.800)
Job involves any basic numeracy/literacy task * College	-12.94***	-10.47**
	(3.505)	(4.141)
Job involves advanced numeracy/literacy tasks	10.40***	7.205***
	(3.115)	(2.621)
Job involves advanced numeracy/literacy tasks * Medium schooling	1.978	-4.807
	(4.636)	(4.067)
Job involves advanced numeracy/literacy tasks * College	6.629*	7.020*
	(3.844)	(3.657)

Heteroscedasticity-adjusted standard errors in parentheses (Huber -White adjustment)
*** p<0.01, ** p<0.05, * p<0.1
The covariates included are those in Table 1 plus the variables reported. Column 1 includes numeric tasks and column 2 reading and writing tasks only.

An alternative explanation for the heterogeneity of results regarding the impact of advanced tasks is a non-classic measurement error, namely, the fact that individuals with primary education could not really be performing complex tasks. Moreover, it is also likely that the results may be affected by the existence of measurement errors, since continuous performance of these tasks is assumed, even though Spanish workers and, in particular, those with low educational levels, are subject to a high level of job turnover which introduces remarkable job instability. Hence, the last job may not be fully representative of the type of labour market experience accumulated throughout the working life. To provide some evidence on this hypothesis we repeat the previous regressions including, as an index of job instability, a dummy variable that takes the value 1 when the worker has had 3 or more different jobs over the past five years. Results, presented in Table 4.5, show that job instability does not seem to have a negative impact on the literacy test results of individuals with low educational level, and that it even reinforces the link between performing basic numeracy tasks and the result of the numeracy test. On the other hand, job instability weakens the relationship between performing advanced tasks in the last job and the result in both tests. Nevertheless, this may be also due to measurement errors - the performance of an advanced task in a short-term job contributes less to the acquisition of cognitive skills, just as a negative impact of job turnover, and the instability that entails, on the acquisition of human capital. A more elaborate analysis of how job instability affects cognitive and economic outcomes is contained in Cabrales, Dolado and Mora (2013).

Table 4.5a. OLS regression of test scores on demographics, schooling, experience and job instability

VARIABLES	(1) Primary schooling Literacy	(2) Medium schooling Literacy	(3) College Literacy
Job involves any basic literacy task	11.36***	4.719	7.773
	(2.627)	(4.470)	(5.103)
Job involves advanced literacy task	4.153	4.517	15.70***
	(2.842)	(3.523)	(2.903)
More than 3 jobs in the last 5 years * Basic tasks	5.934	2.477	-4.718
	(5.634)	(9.225)	(8.224)
More than 3 jobs in the last 5 years * Advanced tasks	13.47*	-12.16	-7.684
	(7.513)	(8.262)	(6.261)

VARIABLES	(4) Primary schooling Numeracy	(5) Medium schooling Numeracy	(6) College Numeracy
Job involves any basic numeracy task	6.982**	6.561	4.962
	(2.795)	(4.409)	(3.433)
Job involves advanced numeracy task	12.07***	13.40***	19.06***
	(3.440)	(3.956)	(2.538)
More than 3 jobs in the last 5 years * Basic tasks	19.19***	4.943	2.673
	(5.961)	(9.354)	(6.743)
More than 3 jobs in the last 5 years * Advanced tasks	-16.29**	-4.207	-4.004
	(8.236)	(9.683)	(5.493)

Source: PIAAC, sample of workers with some experience 25-65
Heteroscedasticity-adjusted standard errors in parentheses (Huber -White adjustment)
*** p<0.01, ** p<0.05, * p<0.1

Moreover, workers with university studies are obviously more likely to hold jobs for which they are overqualified. And in this case, we could expect that performing basic tasks, or even advanced tasks at work would not produce a positive effect on the accumulation of cognitive skills. To test this conjecture, we use the information provided by the PIAAC survey on the degree of overqualification claimed by the workers themselves regarding their last job.

Table 4.5b shows that the measurement of overqualification used does not seem to affect the statistical relationship between the content of the tasks performed in the job and the results obtained in the tests. In an additional specification, in which both indexes of of job turbulence and of overqualification are included, the former have limited explanatory power, while job instability makes the performance of advanced tasks to be less relevant for the test results - a result similar to that obtained in Table 4.5a-. These results nevertheless should be qualified since the quality of the overqualification index, which is reported by the respondent and may reflect the influence of other characteristics, is questionable. But with this qualification, it appears that job rotation is a more relevant factor in explaining the relatively weak relationship between the tasks performed at work and the results of the tests results in the case of individuals with a university degree.

Table 4.5b. OLS regression of test scores on demographics, schooling, experience and job instability

VARIABLES	(1) Primary schooling Literacy	(2) Medium schooling Literacy	(3) College Literacy
Job involves any basic numeracy/literacy task	12.76*** (2.591)	4.011 (4.314)	4.590 (4.643)
Job involves advanced numeracy/literacy task	6.067** (2.860)	1.077 (3.584)	15.99*** (2.886)
Reports being overqualified * basic tasks	-8.030 (7.256)	-0.882 (12.86)	11.85 (12.37)
Reports being overqualified * advanced tasks	9.468 (9.185)	9.266 (9.319)	-6.295 (7.873)
Reports being underqualified * basic tasks	-0.172 (16.35)	23.59* (13.49)	27.80 (18.24)
Reports being underqualified * advanced tasks	-9.152 (12.45)	2.720 (14.25)	-13.12 (11.89)
VARIABLES	(4) Primary schooling Numeracy	(5) Medium schooling Numeracy	(6) College Numeracy
Job involves any basic numeracy/literacy task	10.65*** (2.823)	9.046** (4.386)	4.165 (3.172)
Job involves advanced numeracy/literacy task	10.55*** (3.419)	8.707** (4.018)	19.36*** (2.477)
Reports being overqualified * basic tasks	-0.343 (7.655)	-7.367 (11.81)	21.21* (12.62)
Reports being overqualified * advanced tasks	-8.909 (13.12)	32.33*** (9.704)	-8.528 (7.544)
Reports being underqualified * basic tasks	-0.529 (11.70)	-18.45 (17.77)	5.986 (11.52)
Reports being underqualified * advanced tasks	-12.68 (11.34)	3.593 (14.94)	-6.594 (9.160)

Source: PIAAC
The covariates reported in Table 1 are included but not shown

FINAL COMMENTS

In this paper we have attempted a first approximation to the data from the PIAAC survey for Spain from a perspective that seeks to document, firstly, the extent to which the educational level and labour market experience of workers are associated with their cognitive skills and, secondly, whether this association is reflected in their earnings. The results, which are very preliminary and therefore require further analysis, suggest that labour market experience is associated with an increase in cognitive skills, especially with respect to the numeracy test results, at the beginning of the working life, specially among the younger cohorts, and in the case of workers with low educational levels. Although there is a clear association between the measurements of cognitive skills provided by the PIAAC survey and workers' wages, the association between education level and labour market experience and wages shows some significant differences with respect to that which exists between the first two variables and the measurements of cognitive skills. For example, contrary to what happens with cognitive skills, labour market experience is associated with an increase in wages which is greater for workers who have completed university studies than for workers with low education level.

In order to try to provide some evidence for the causes of this difference, we have proposed that the type of tasks performed at work, job stability, and the degree of mismatch between the qualifications of workers and the job requirements, are factors that could explain why the effect of labour market experience on the accumulation of cognitive skills is different for workers of different education levels. The first results regarding this question show that, indeed, the type of tasks performed at work, and job stability help to explain these differences. However, for this purpose, overqualification does not seem very significant. Concretely, within the group with primary education, the results in numeracy tests are 15 points higher among individuals who perform basic numeracy tasks at work - using a calculator, calculating percentages-. Within this same group, there is a statistical association between the execution of basic literacy tasks - writing emails, reading some type of material - and the results in the literacy test. These basic tasks contribute very little to the result of numeracy or literacy tests of the group of respondents with university studies. By contrast, the results in the tests are higher among the group of qualified individuals who perform advanced tasks - numeracy or literacy - and who have rotated less across jobs. However, an overqualification index based on the worker's own estimation suggests that mismatch plays a very reduced role in this regard. These results do not have a causal interpretation, since we do not have any information about the cognitive skills before entering the job market. For example, it could be argued that individuals with higher innate skills get jobs with more sophisticated content, regardless of their educational level. However, several of the results that we found reject the idea that the selection in the labour market explains all of our results. Individuals with basic education that perform advanced tasks get a "lower" reward in their results than those who carry out basic tasks. The performance of basic tasks, which predictably are less subject to returns to scale, increase the results of both numeracy and literacy tests even among workers with low education who have rotated between jobs. A model in which the "best workers" reach “better, more stable jobs” would not generate this result.

If confirmed, these findings have some implications for the design of active policies and other employment policies. Firstly, the fact that specific tasks contribute to increasing cognitive skills and others not, should shape the direction of job training. Secondly, the fact that job stability is important in encouraging learning on the job, especially among workers with higher educational levels, is one more element to take into account when addressing the problem of excessive job turnover that characterizes the Spanish labour market.

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5. Over-qualification of university graduates and social mobility

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Abstract

Is university graduates' over-qualification related to their social background? In order to answer this question, five indicators were drawn up on over-qualification, three of which are common in the literature (objective, subjective and statistical) and two permitted by PIAAC (statistical over-qualification in reading and numerical skills). The results are not conclusive as the relationship can be seen in the cases of objective and subjective over-qualification, but not in the rest. On the other hand, a further look was taken at social mobility studies and it was found that once the level of studies is taken into account then social origin has little influence on the probability of getting a high qualification job. In other words, social origin seems to be intensely linked to the educational attainment, but the links between educational attainment and occupation are much weaker.

Keywords

Over-qualification, job market, human capital, social mobility, inequality of educational opportunities, Boudon, Goldthorpe, Bourdieu, educational mismatch.

INTRODUCTION

The debate around over-qualification emerged in the USA in the 70s. After the upper education boom in the second half of the 20th century, young graduates found it difficult to get into the job market (Freeman 1976). The research scope is therefore the result of sensitivity to a social question regarding people that, after having invested time, effort and money on training, do not get a job that matches their qualifications. The problem is greater in Spain than in most OECD countries according to estimations made in different studies (Quintini 2011; OECD 2013), as this phenomenon has been going on for decades (Dolado, Felgueroso & Jimeno 2000).

Over-qualification is a problem of personal frustration (Kucel 2011) as well as an economic problem as it increases the equilibrium unemployment rate and reduces productivity for both companies and the country (Quintini 2011). The main theoretical debates around over-qualification from the review of works by Sala (2011), Kucel (2011), Leuven and Oosterbeek (2011) and Quintini (2011) are summarised briefly below. We will subsequently propose five over-qualification indicators. The aim of this study will be to work out whether social origin influences the probability of university graduates being over-qualified. Therefore, both over-qualification studies and social mobility studies are used in the approach.

From human capital theory, any mismatch between training requirements for the position and qualification should be understood as provisional. The basic hypothesis of this theoretical proposal is that salaries are paid according to the employees' marginal productivity, so that if a mismatch exists this is due to the time required for the employee and the businessman to find an equilibrium point between marginal productivity and wages (Becker 1964). Since evidence shows that this mismatch is lasting, it is attributed to unobserved employee characteristics that reduce their productivity (Mincer 1974). In this respect, the lower wages could be due to the fact that the over-qualified worker's productivity is lower than for workers who hold a position matching their qualifications. This lower productivity might be due to different factors, such as less effort or motivation from the worker or due to the heterogeneity of educational qualifications at the same level. Some studies show that over-qualification is greater in some university qualification branches than others, inferring that this is not the result of a mismatch but recognition that an equivalent formal qualification can hide clearly different work-based skills (Barone & Ortiz 2011). What's more, this phenomenon would explain the rise in wage differences for university graduates.

We can interpret the equilibrium theory (Pissarides 2000) as a specific case of the human capital model. The theory insists on the importance of correctly matching jobs to employees since companies' hiring processes and employees’ job searches are both costly processes. Workers will continue to change jobs until they manage to match their qualification. Job mobility, either between companies or within the same company, will thus be greater among overqualified workers who have still not completed this matching process.

Signalling theory (Spence 1973) considers that training does not improve workers' productivity but gaining an educational qualification signals that they are more productive. The educational qualification is a solution to a problem of information asymmetry as the businessman does not know about the employee's productivity before they are employed. This theory interprets the workers' investment in education in the following way: it supposes that there is a correlation between educational performance and work productivity as people with more capability require less effort to achieve their educational goals and their greater capability will also be noted when they perform their job. For this reason, educational qualifications should be interpreted as a sign of productivity that the worker 'purchases' with their effort, capability and resources, to send a message to business owners. Over-qualification might occur whilst the performance associated with the signal (the educational qualification) is greater than the cost of obtaining it. These costs should take into account the workers' capability and their effort as well as variations in the cost of studying, so that changes in this cost (such as the course price or the opportunity costs of studying) will affect over-qualification; as the cost of studying rises, over-qualification will decline.

Another explanation can be found in Thurow's job market model (1975) and his theory known as the job-competition theory. From this point of view, wages depends more on the characteristics of the job than on the worker's characteristics. For this author, there are two queues in this market to select who will take up a job vacancy. One is for jobs and the other is for workers and both are determined differently. The requirements for doing the job properly are really achieved in the company, which is where the necessary skills are learned. Workers are organised according to series of attributes that indicate how difficult they will find it to learn to do their future jobs. Level of studies is one of these attributes but there are also other relevant aspects such as experience. The workers' queue is ordered according to this type of characteristics so investment in education is not so much a question of an intrinsic improvement in productivity but a chance of improving relative position over other workers. As mentioned by Sala (2011), although this seems to be like the signalling model in the job market (investment in education does not improve the worker's productivity), it is different in that Spence's model can reach a point when the investment in the educational signal reaches an equilibrium with the expected return from education. However, in Thurow's model, the decision is not so much a question of return per se, but of relative position compared to other workers, so it is a model that is more consistent with over-qualification as a permanent phenomenon, as opposed to the previously mentioned theories.

Another approach is Sattinger's assignment theory (1993) that considers arguments from the theory of human capital and from competition. For this theory, the wage is defined by both the workers' productivity and by the productivity of the job itself. A specific job will have lower and upper wage limits and within this range a lack or excess of education can contribute to reducing or increasing the expected return. This theory is particularly used when studying the influence of educational mismatch on wage performance.

These different theories take into account the existence of over-qualification but in this research we will be examining something much more specific: to what extent is over-qualification the result of inequality stemming from socioeconomic origin. Or in other words, is the probability of a university graduate being over-qualified higher or lower depending on their social origin? Kucel (2010) presents this approach to over-qualification based on social mobility studies, an area less explored than the affects over-qualification has on salary, on psychological wellbeing or political approaches. Bukodi & Goldthorpe (2011) propose that whilst the phenomenon of over-qualification is linked to social origin and there is an increasing number of people with lower social origin, the relationship between educational level and occupation could be weakening. This would invalidate the functionalist hypothesis according to which the nature of economic development itself and the search for efficiency should strengthen this relationship over time (Treiman 1970).

This mismatch could be happening due to the fact that there are occupations that, in addition to highly specialised knowledge and "hard" skills (maths and reading-writing), also require "soft" skills (social skills, leadership, influence and autonomy among others) that are formed to a large extent in medium and high social classes more than in working classes. From this point of view, the effect of social origin would be measured by generating relevant characteristics for the businessman who perceives some workers to be more capable of generating business than others. Bourdieu (1991) already brought up this question, particularly highlighting the importance of lifestyle affinities (social class *habitus*) among workers, on the one hand, and businessmen or customers on the other in certain working sectors. For Bourdieu, social capital is also important, making it easier to access information on the job market, and he is critical about the contribution these non-cognitive factors make to productivity. In the end it would just be another way of legitimising the arbitrary and unequal distribution of socioeconomic resources within a society.

METHODOLOGY

The selected sample will be the people in PIAAC who are working in the week prior to filling in the survey, aged between 25 and 65 years old (2886 cases). This selection takes into account the majority of the population who have achieved their maximum level of education and it avoids the problem of disparate skills among the working and non working population. The main independent variable in this research is the level of studies held by the interviewee's father, since the father's influence on work mobility processes may be greater than the mother's. This is due to the fact that for most of the population in the study very few of the mothers worked. Given that participation in the job market gives access to social networks and tacit knowledge, it seems more relevant to take into account the information on the fathers. We do not have data on the fathers' occupation which is one of the main characteristics considered in mobility studies.

The literature operationalizes over-qualification in three ways that are described differently. The first is a normative or based on "objective" job analysis. The second is self-declared or subjective, and the third is statistical. The normative definition of a job position or objective definition consists of accurately defining the training requirements for the job by determining whether this matches the level of training held by the person performing it. Applying this method properly requires a detailed job study that is beyond the scope of this research and that in other research requires a detailed catalogue of occupations and their training requirements. With more aggregate data, authors such as García Montalvo & Peiró (2009) propose grouping together occupations and classifying them with one digit to give a general idea of the qualification requirements for the jobs. This is the method followed in this research where it has been considered that a person's educational level might match a two-digit occupational category in the international standard classification of occupations (ISCO 2008). The problem that emerges when assigning a level of studies to an occupation is that it produces considerable measurement error (Glebbeek 1993), among other reasons, due to the fact that the higher the level of aggregation of the occupations, the more heterogeneous the level of difficulty might be and the type of skills associated with it.

In the self-declared (or subjective) method, workers are asked about the training requirements for their job. This option has the disadvantage that, on the one hand, people might over-estimate the difficulty of the task they perform (Sloane 2003). Regarding statistical measurement, it takes the average number of years of schooling for the persons in a particular job as a reference (or another more robust statistic for a central trend) on the supposition that this will be the optimum training required to perform it. Anyone who is above a standard deviation is considered to be over-qualified and the inverse situation is known as under-qualified. This way of measuring is quite practical as it does not involve a detailed study of the occupations nor is it subject to bias in the workers' answers. However, it is not problem-free as the decision over which standard deviation to use as a cut-off point remains arbitrary. In addition, it also runs the risk of creating an artefact effect as it can lead to situations where many people with high levels of studies hold certain jobs with low training requirements so this measurement would give a lower level of over-qualification than actually exists (or vice versa). In addition, over-qualification will depend on how schooling is distributed in each occupation; the operationalization of the concept could produce over-qualification measurements. The nature of the PIAAC study allows us to take a closer look at this over-qualification measurement in its different forms. On the one hand we can use the standard method, transforming educational level into years of schooling [*YRSQUAL*] and performing the relevant operations. On the other hand, the PIAAC information provides a new line of attack since, apart from the educational qualification, we can also use the skills level measured in the tests as a qualification indicator. We created these for reading [PVLIT1] and maths [PVNUM1] skills following the statistical definition of educational mismatch (the individual's score is higher or lower by a standard deviation from the average of the people in the job).

In PIAAC, the interviewees are asked about the educational level required to perform the job *[D_Q12A].* This might generate some confusion among anyone who studied in previous educational systems as their knowledge of the current system might be limited and this might lead to mistakes. It should be noted that the students in the research population have studied under three different education systems: *Moyano Law* (for those born between 1947 and 1960), the General Education Law (LGE, for those born between 1961 and 1979), and the Organic Law for Education System Ordinance (LOGSE, for those born between 1985 and 1987). Anyone born between 1980 and 1984 fell in the transition period between the last two systems. Statistical homogenization of qualifications can hide substantially different characteristics, including the fact that the minimum years of schooling to obtain the "Graduado Escolar" (School Grade) (LGE) used to be eight and is now ten, to assimilate it into the new ESO Graduate Certificate[1].The results from these educational mismatch indicators are presented in Table 5.1, based on the working population between 25 and 65 years old. As is usual in this type of studies, the different definitions give diverging results on educational match. Except for the subjective measure (or self-reporting) which produces the lowest match, with 55.1%, the rest fall within a range between 67.6% for "statistical over-qualification" and a 72.4% in the "objective over-qualification" (the number of cases varies due to the absence of information in some questions).

Table 5.1. Distribution of the different types of educational mismatch with jobs

Type of over-qualification	Under-qualified	Matching	Overqualified	Total (%)	Total (N)
Objective over-qualification	13.5%	72.4%	14.1%	100.0%	2872
Subjective on educational qualification	24.2%	55.1%	20.7%	100.0%	2318
Statistical over-qualification	18.6%	67.6%	13.8%	100.0%	2878
Statistical on reading	16.2%	68.4%	15.4%	100.0%	2885
Statistical on maths	14.9%	70.2%	14.9%	100.0%	2885

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

As we can appreciate in Table 5.2, 73% of over-qualified workers meet one or two criteria, so the different ways of operationalizing this concept offer very different results.

[1] It is appropriate to draw attention to two particularly problematic homogenizations. On the one hand, when changing from the Moyano Law to the LGE, qualifications for experts and others, such as teachers, that could be concluded at age 18 or before were considered to be ISCED5B, or the equivalent of upper education, which usually finishes when students are 20 or 21. On the other hand, when going from the LGE to the LOGSE, there was an assimilation of FPII, which did not require completing the Baccalaureate and which ended at age 18, into the Higher FP, which finishes when the students are 20 and mainly taken by post-Baccalaureate students. Therefore, homogenising these qualifications supposes that two or three additional years of schooling do not produce different performance both from the perspectives of work productivity and skills in reading and maths.

Table 5.2. Coincidence frequency for the different types of over-qualification in a single person

No. of positive over-qualification indicators	Frequency	Percentage
1	426	44.7
2	269	28.3
3	159	16,7
4	63	6.6
5	33	3.5
Total	**952**	**100**

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

The level of studies for the interviewees is a decisive variable in the study. Table 5.3 breaks this down, also adding the father or guardian's level of studies. We can see the well-known relationship between social background and level of studies. The percentage of people whose father did not complete studies but who manage to get a degree or a Masters is 11.0%, whilst this probability is 41.4% if their father has been to university. On the contrary, children of a father who did not go to university do not go beyond primary level in 17.2% of cases, whilst this percentage is just 2.2% for children whose fathers went to university. It should be highlighted that the differences are smaller if we break down levels within upper education where Experts or assimilates, Diploma holders and Technical Engineers score 10.6% for children of fathers with no studies and 26.1% of children with graduate fathers.

Table 5.3. Level of studies of interviewee (disaggregated) according to their father or guardian's level of studies

	Father or guardian's level of studies			
	ISCED 1, 2 and 3C Short	**ISCED 3 (without 3C short) and 4**	**ISCED 5 and 6**	**Total**
Primary or less (ISCED 1 or less)	17.2%	2.0%	2.2%	13.5%
Lower secondary (ISCED 2, ISCED 3C - short)	25.7%	15.0%	3.1%	21.8%
Higher secondary (ISCED 3A-B, C - long)	22.0%	26.4%	14.4%	21.8%
Post-compulsory, not higher (ISCED 4A-B-C)	1.7%	0.7%	2.8%	1.7%
Higher vocational training (ISCED 5B)	11.3%	8.5%	6.6%	10.4%
Diploma, Technical Eng. (ISCED 5A1)	10.6%	18.3%	26.1%	13.3%
Degree (ISCED 5A2)	11.0%	27.7%	41.4%	16.6%
PhD (ISCED 6)	0.5%	1.4%	3.4%	1.0%
Total	100%	100%	100%	100%
	N=2184	N=382	N=320	N=2887

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

Due to the fact that this level of detail leads to very small sub-samples, the later research went on to group the level of studies into four categories: ISCED 1 or less, ISCED 2, 3 or 4, ISCED 5B and ISCED 5A and 6 (as already shown in Table 5.4). The price to pay for getting a larger sample size is greater heterogeneity in each educational level, particularly in secondary education (ISCED 2, 3 or 4) and in upper education (5A and 6), which should be taken into account when interpreting the data. In order to minimise this problem statistical over-qualification calculations are performed for university studies by separating levels 5A1 and 5A2, although the results appear grouped together with the data.

In addition to this approach of using three typical indicators from the literature plus the two that we drew up with PIAAC, we have also considered the match between educational qualifications and the four major job groups created for the study, namely: qualified jobs, semi-qualified white-collar jobs, semi-qualified blue-collar jobs and low qualification jobs (Table 5.4). If we take a look at who has university studies, we could state that 25.4% could be considered over-qualified.

Table 5.4. Type of occupation per interviewee's level of studies

	Level of studies (4 categories)				
	ISCED 1 or less	ISCED 2,3 or 4	ISCED 5B	ISCED 5A1-5A2-6	Total
Qualified	10.6%	26.6%	32.1%	75.6%	36.5%
Semi-qualified white-collar	32.1%	44.8%	37.9%	20.0%	31.9%
Semi-qualified blue-collar	34.3%	17.5%	24.4%	2.0%	19.5%
Basic Occupations	23.0%	11.1%	5.6%	2.4%	12.1%
Total	100%	100%	100%	100%	100%
	N=1044	N=679	N=301	N=897	N=2921

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

The remaining variables considered in this study are gender, age, nationality and experience on the job, which are all individual characteristics associated with over-qualification. They were used to compare their effect to social origin and the type of skills associated with the tasks performed in their job. In the literature, the effects of gender tend to point towards greater over-qualification among women, particularly if they are married. This can be explained by the fact that male careers tend to be more stable and better paid than female careers. Women tend to make their decisions based more on work/life balance, whilst men make decisions guided to a greater extent by work issues. Thus, it is expected that as it gets easier to balance life and work, fewer differences will be found between men and women. Regarding age, to the extent that this is associated with career, it is expected that as people get older, over-qualification will fall. However, this relationship cannot be linear due to complex relationships between the development of cognitive skills throughout life and period effects (Desjardins and Warnke 2011). On the one hand, as people age fluid intelligence is dropping whilst crystallised intelligence improves, and to the extent that crystallised intelligence becomes obsolete to solve problems, older people, despite maintaining their educational credentials, can lose certain work potential due to a combination of their knowledge becoming obsolete and finding it difficult to acquire new knowledge. We would therefore be in a case that might be registered as over-qualification from the point of view of educational qualification but not so much from the skills viewpoint. Regarding nationality, this can be related to over-qualification for three reasons. On the one hand, when performing certain jobs national particularities can come into play, such as the legal profession. On the other, although these differences can be minimal, it may be difficult to get accreditation of educational credentials, such as the case of medicine. Finally, it is possible that discrimination may also exist. Regarding job experience, it would be expected that if the match has indeed been achieved, both business owner and worker will have less incentive for work mobility, whether it be internal promotion or rotation among companies.

Concerning the skills developed on the job, two variables have been created from the information provided by the interviewees for the following indices elaborated with answers to different questions: use of information technologies at work (ICTWORK), influence over other people at work (INFLUENCE), need of numerical skills (NUMWORK), reading skills (READWORK), writing skills (WRITWORK), planning skills (PLANNING) or if it is necessary to learn new tasks (LEARNATWORK). With these indices two factors were extracted through principal component analysis with varimax rotation (see appendix). The first factor can be considered as "hard skills", which include working with ICTs, making calculations or reading and writing reports. The second factor includes "soft skills" associated with planning, social relationships and learning. The factor extraction method leads to factors being uncorrelated, dimensionless, and with a canonical normal distribution (zero mean and unit variance).

RESULTS

Table 5.5 presents the relationship between social origin and the over-qualification rate. The greater the father's educational level, the lower the over-qualification (both subjective and objective). However, the expected relationship was not seen in the three statistical definitions. In the case of years of schooling, the differences are small, whilst the skills differences are clearly contrary to expectations, with a greater rate of over-qualification as the father or guardian's level of studies increases. As we will see below (Table 5.15), this might be due to the fact that at lower educational levels, people with a higher social origin demonstrate a higher level of skills than the rest of the population. In so far as many jobs are decided on by formal qualifications, persons with a high social origin and low qualifications do not benefit in this point from their higher skills level. This finding is consistent with the signalling and credentialism theories but not with the human capital theories, as it shows that the job market tends to recognise educational qualifications over skills. For the population as a whole, the relationship is contrary to expectations, but this is due to a compositional effect, as over-qualification is greater at higher educational levels, where there are greater numbers of people with university qualifications.

Table 5.5. Father or guardian's level of studies and rate of over-qualification for university graduates and for the population as a whole (25-65 years old)

		Father or guardian's level of studies			
		ISCED 1, 2 and 3C - short	ISCED 3 (without 3C - short) and 4	ISCED 5 and 6	Total
ISCED 5A1-5A2-6	Objective	28.3	25.8	19.9	25.7
	Subjective	41.2	37.9	31.6	38.2
	Statistical (years of schooling)	28.7	32.8	27	29.1
	Statistical on reading	23.2	21.8	30.4	24.8
	Statistical on maths	20.3	24.1	27.8	23
Total	Objective	12.8	17.3	17.5	14
	Subjective	18.9	26.7	30.5	21.3
	Statistical (years of schooling)	11.5	19	22.9	13.8
	Statistical on reading	13	21.1	28.2	15.7
	Statistical on maths	13.4	22	24.9	15.8

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

For the differences between men and women (Table 5.6), there is no common pattern here either for the different definitions of over-qualification. Among university graduates, over-qualification is very similar for men and women if we define it as objective or statistical in years of schooling, but it is greater for men when it is defined as subjective or by skills, both in reading and maths. Due to the fact that the gender differences are only subjective, they could be due to the fact that there is a bias for this attribute in how men and women assess how appropriate they are for the job, or that the peculiarities of the occupational tasks differ by gender.

Table 5.6. Rate of over-qualification by gender, for university graduates and for the population as a whole

		Gender		
		Men	Women	Total
ISCED 5A1-5A2-6	Objective	26.1	25.3	25.7
	Subjective	42.3	35.3	38.4
	Statistical (years of schooling)	28.6	29.4	29
	Statistical on reading	29.5	19.9	24.4
	Statistical on maths	30.2	15.9	22.7
Total	Objective	13.6	14.1	13.9
	Subjective	18.8	23.9	21.2
	Statistical (years of schooling)	13	14.4	13.6
	Statistical on reading	17.2	13.5	15.6
	Statistical on maths	19	11.5	15.6

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

Over-qualification among university graduates is greater among those born abroad[2] (Table 5.7), except for reading skills. The greatest differences occur in objective over-qualification and

[2] From the whole sample, under thirty people answered that they achieved their top level of education abroad (CNT_H), so the sample is not big enough to establish differences using this criterion.

statistical in years of schooling. For the population as a whole, over-qualification of those born abroad is greater, except for both reading and maths skills.

Table 5.7. Rate of over-qualification according to nationality for university graduates and the population as a whole

Interviewee's level of studies	Type of over-qualification	Gender		
		Men	Women	Total
ISCED 5A1-5A2-6	Objective	26.1	25.3	25.7
	Subjective	42.3	35.3	38.4
	Statistical (years of schooling)	28.6	29.4	29
	Statistical on reading	29.5	19.9	24.4
	Statistical on maths	30.2	15.9	22.7
Total	Objective	13.6	14.1	13.9
	Subjective	18.8	23.9	21.2
	Statistical (years of schooling)	13	14.4	13.6
	Statistical on reading	17.2	13.5	15.6
	Statistical on maths	19	11.5	15.6

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

Work experience on the job is the only characteristic that shows a consistent pattern out of all the over-qualification indicators (Table 5.8), in the expected sense: more years working in this position lead to less over-qualification, although in some cases the greatest difference is between 0-3 years (maximum duration of temporary contracts) and the rest of experience. The work in this volume by Cabrales, Dolado & Mora (2013) shows a clear negative relationship between the type of contracting and the level of skills. This result is consistent with the adjustment theory where over-qualification should drop over time, because as its very name suggests, it is a labour adjustment problem.

Table 5.8. Rate of over-qualification according to experience in current job, for university graduates and for the total

Interviewee's level of studies	Type of over-qualification	Experience in current job			
		0-3 years	4-8 years	9 + years	Total
ISCED 5A1-5A2-6	Objective	33.3	25.2	22.5	26
	Subjective	48.2	37.6	33.7	38.5
	Statistical (years of schooling)	39.7	27.2	26.2	30
	Statistical on reading	29.1	25.9	22.1	24.8
	Statistical on maths	26.3	22.4	21.4	22.9
Total	Objective	16.3	14.1	13.4	14.4
	Subjective	25.3	22	18.3	21.2
	Statistical (years of schooling)	17.8	12	12.6	13.9
	Statistical on reading	18.4	15.3	15	16
	Statistical on maths	16.9	16.8	15.2	16.1

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

As far as age is concerned (Table 5.9), over-qualification of university graduates continues to show an inverted U relationship in all types of over-qualification except for objective. This pattern is similar to what was seen for cognitive skills as people age, since the so-called fluid intelligence (capacity to innovate) and crystallised intelligence (capacity to make use of experience) evolve differently over as people age and the combined peak of both occurs in middle age.

Table 5.9. Rate of over-qualification by age group, for university graduates and for the population as a whole

Interviewee's level of studies	Type of over-qualification	Age groups				Total
		25-34	35-44	45-54	55-65	
ISCED 5A1-5A2-6	Objective	27,5	29,3	19,2	25,1	25,7
	Subjective	40,2	42,2	35,8	27,8	38,4
	Statistical	30,1	31,7	26,0	24,7	29,0
	Statistical on reading	22,5	28,6	24,8	14,7	24,4
	Statistical on maths	21,1	26,2	23,7	12,1	22,7
Total	Objective statistical	16,8	16,9	10,4	8,4	13,9
	Subjective	24,5	23,4	19,8	10,6	21,2
	Statistical	16,3	16,0	11,3	8,0	13,6
	Statistical on reading	16,2	19,4	14,7	7,2	15,6
	Statistical on maths	17,7	19,3	13,8	7,1	15,6

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

Based on these standard definitions, we have checked to see what types of skills are demanded in each occupation, working from scores for the factors shown in the appendix. In Table 5.10 we can see the average of the first factor (canonical normal distribution) that groups together the information for the whole set of job requirement, particularly any information related to hard skills. People whose father went to university say that they are in jobs with greater skills' requirement, similar to the level of studies of the interviewees. The standard deviations from the average are between 0.05 and 0.2 so they are not excessively high.

Table 5.10. Average score for the "hard" and generic skills' requirements factor for the position, according to the interviewee and their father's level of studies.

Interviewee's level of studies	Father or guardian's level of studies			
	ISCED 1, 2, and 3C - short	ISCED 3 (without 3C - short), and 4	ISCED 5 and 6	Total
ISCED 1 or less	-0.28	-0.15	0.19	-0.27
ISCED 2, 3 or 4	-0.02	0.02	0.17	0
ISCED 5B	-0.1	-0.12	-0.22	-0.11
ISCED 5A1-5A2-6	0.42	0.41	0.34	0.4
Total	-0.04	0.16	0.27	0.02

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

In Table 5.11 we can appreciate the results for the factor that comprises "soft" skills. We can see that for persons with low educational qualifications (secondary studies or less), the level of non-cognitive requirements for the position is related positively with the father's level of education. However, for higher studies, the higher the father's level of education, the lower these skills tend to be, like in "hard" skills, but the differences are less. This could perhaps be due to a selection bias, in that people with a low social origin who achieve a university qualification are more likely to be selected based on non-cognitive factors than people with a high social origin. This seems to contradict the argument throughout the literature quoted in the introduction, according to which, people with a high social origin would have higher non-cognitive skills.

Table 5.11. Average score for the "soft" and generic skills' requirements factor for the position according to the interviewee and their father's level of studies

Interviewee's level of studies	Father or guardian's level of studies			
	ISCED 1, 2, and 3C - short	ISCED 3 (without 3C - short), and 4	ISCED 5 and 6	Total
ISCED 1 or less	-0.29	-0.15	0.13	-0.28
ISCED 2, 3 or 4	-0.03	0.02	0.08	0
ISCED 5B	-0.07	0.03	-0.19	-0.07
ISCED 5A1-5A2-6	0.43	0.41	0.37	0.41
Total	-0.06	0.19	0.27	0.01

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

Another way of searching for possible over-qualification differences is to work out the average number of years of schooling by occupation (another way of approaching statistical over-qualification). As we can see in Table 5.12, relevant differences cannot be seen meaning that the persons who have achieved a certain level of education are in occupations where average schooling in similar. It should be noted that the difference in the average years of schooling between the four educational levels is four academic years (10.6 to 14.4), which is not a considerable difference in absolute terms.

Table 5.12. Average years of schooling for persons in each occupation by parent and interviewee's education level

Interviewee's level of studies	Father or guardian's level of studies			
	ISCED 1, 2, and 3C - short	ISCED 3 (without 3C - short), and 4	ISCED 5 and 6	Total
ISCED 1 or less	10.6	11.1	10.8	10.6
ISCED 2, 3 or 4	11.8	12	11.9	11.8
ISCED 5B	12.1	12.4	12.3	12.2
ISCED 5A1-5A2-6	14.3	14.3	14.6	14.4
Total	11.9	13	13.8	12.2

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

Given the lack of clear results using these procedures, we studied the relationship between social origin, level of studies and occupation divided into major groups, which is more common in social mobility studies. Starting with the relationship between social origin and educational achievement (Table 5.13), we can see the strong relationship between them, as repeatedly reflected in social research (Breen & Jonsson 2005). The probability of having a university education is 70.9% for children of university graduates whilst only 22.0% for children of persons with lower levels of studies. Regarding the probability of not going any further than primary studies, this is 5.3 and 42.9% respectively.

Table 5.13. Level of studies achieved by the interviewee (%), according to father or guardian's level of studies

Father or guardian's level of studies	Interviewee's level of studies					
	ISCED 1 or less	ISCED 2, 3 or 4	ISCED 5B	ISCED 5A1-5A2-6	Total	
ISCED 1, 2, 3C	42.9%	23.7%	11.3%	22.0%	100%	2184
ISCED 3 and 4	17.0%	27.1%	8.5%	47.3%	100%	382
ISCED 5 and 6	5.3%	17.2%	6.6%	70.9%	100%	320
Total	35.3%	23.5%	10.4%	30.8%	100%	2887

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

Table 5.14 demonstrates the probability of achieving a certain occupational level (as a percentage) according to the father and interviewee's level of education in so much that it is a typical table analysing social mobility. Overall, we can appreciate a remarkable influence between social origin and occupational destiny: the probability of attaining a qualified occupation varies considerably depending on the parent's level of education to the point that the probability of doing this job is over double for anyone coming from a family where the father is a university graduate compared to anyone from a family with low levels of education (68 and 32%, respectively), whilst the probability of doing a basic job is almost three times higher for anyone coming from families with a low level of education than from a high level (14 and 5%, respectively).

This inequality of opportunities operates fundamentally by means of the education system as we can appreciate that the differences within each educational level are relatively small and following the direction predicted by social mobility theories. At average educational levels for the interviewees there is practically no inequality of opportunities due to social origin. However, at the highest and lowest educational levels, this influence is much more evident. On the one hand, if the interviewees have the lowest level of studies, the probability of getting a qualified job is almost double for people with graduate fathers than anyone whose father did not go to university (19.9 vs. 10.5%), so from this point of view, under-qualification is greater in people with high social origin. On the other hand, persons with higher university studies who come from families with higher educational levels have greater probability of 'matching' a qualified job than people who have grown up in families with a lower level of education (84.6 and 71.5%, respectively).

Table 5.14. Type of occupation achieved by the interviewee (as a %), according to father or guardian's level of education

Interviewee's level of studies	Father or guardian's level of studies	Type of occupation held by interviewee					
		Qualified	Semi-qualified, white-collar	Semi-qualified, blue-collar	Basic Occupations	Total (%)	Total (N)
ISCED 1 or less	ISCED 1, 2 and short 3	10.5%	31.3%	34.7%	24%	100%	930
	ISCED 3 (without 3C - short) and 4	14.6%	46.0%	30.8%	9%	100%	65
	ISCED 5 and 6	19.9%	32.0%	13.6%	35%	100%	17
	Total	10.9%	32.3%	34.1%	22.7%	100%	1013
ISCED 2, 3 or 4	ISCED 1, 2 and short 3	26.1%	44.1%	19.4%	10%	100%	516
	ISCED 3 (without 3C - short) and 4	29.8%	44.9%	12.5%	13%	100%	102
	ISCED 5 and 6	29.1%	46.4%	10.3%	14%	100%	55
	Total	26.9%	44.4%	17.6%	11.1%	100%	673
ISCED 5B	ISCED 1, 2 and short 3	32.1%	36.8%	24.9%	6%	100%	246
	ISCED 3 (without 3C - short) and 4	33.4%	46.7%	18.2%	2%	100%	33
	ISCED 5 and 6	30.6%	39.5%	24.5%	5%	100%	21
	Total	32.1%	38.0%	24.2%	5.6%	100%	300
ISCED 5A-6	ISCED 1, 2 and short 3	71.7%	23.3%	1.5%	4%	100%	480
	ISCED 3 (without 3C - short) and 4	74.9%	20.9%	2.1%	2%	100%	179
	ISCED 5 and 6	84.6%	12.5%	2.5%	0%	100%	225
	Total	75.6%	20.1%	1.9%	2.4%	100%	885
Total	ISCED 1, 2 and short 3	30.2%	33.2%	22.6%	14%	100%	2173
	ISCED 3 (without 3C - short) and 4	48.9%	33.9%	11.2%	6%	100%	379
	ISCED 5 and 6	68.0%	21.2%	5.9%	5%	100%	318
	Total	36.8%	32.0%	19.3%	12.0%	100%	2870

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

With these results, the relationship between social origin, educational achievement and professional career show that social origin particularly operates through differences in the probability of accessing a particular level of education, but once they graduate, the influence of social origin is low. In other words, the inequality of opportunities due to social origin is strong in education and mediated by education in their working life.

How far does the different probability of achieving an occupation of a certain level depend on the skills level not reflected in the educational qualification? That very might be the case, although we should be wary when analysing data as the sub-samples are very small (as seen in the totals in the previous table). To avoid this problem, we can focus on analysing only university graduates: we can appreciate that the higher the parent's level of education, the greater the performance in reading, so the same level of education can be associated with a different skills level depending on social origin.

Table 5.15. Average score for reading skills according to interviewee's level of studies, their occupation and their father or guardian's level of studies

Interviewee's level of studies	Father or guardian's level of studies	Type of occupation held by interviewee				
		Qualified	Semi-qualified, white-collar	Semi-qualified, blue-collar	Basic Occupations	Total
ISCED1 or less	ISCED 1, 2 and short 3	243.4	232.5	235.0	225.0	232.8
	ISCED 3 (without 3C - short) and 4	277.6	255.7	253.1	228.6	255.7
	ISCED 5 and 6	291.5	242.2	229.9	238.8	249.1
	Total	247.8	234.8	236.0	225.5	234.5
ISCED 2, 3 or 4	ISCED 1, 2 and short 3	259.2	257.4	255.1	248.9	256.6
	ISCED 3 (without 3C - short) and 4	273.8	261.6	271.2	253.1	265.3
	ISCED 5 and 6	287.6	281.5	253.1	266.1	278.1
	Total	264.1	260.1	256.8	251.4	259.7
ISCED 5B	ISCED 1, 2 and short 3	274.5	262.3	264.9	246.4	265.9
	ISCED 3 (without 3C - short) and 4	270.1	267.6	281.9	281.1	271.3
	ISCED 5 and 6	271.0	279.8	269.2	287.0	274.9
	Total	273.8	264.3	266.6	250.3	267.1
ISCED 5A-6	ISCED 1, 2 and short 3	290.5	284.2	254.1	261.4	287.5
	ISCED 3 (without 3C - short) and 4	292.6	278.5	277.1	255.9	288.6
	ISCED 5 and 6	300.8	297.6	299.4	202.8	300.0
	Total	293.9	285.1	274.7	258.0	290.9
Total	ISCED 1, 2 and short 3	275.1	252.1	243.1	232.3	254.3
	ISCED 3 (without 3C - short) and 4	287.5	265.9	264.7	248.2	275.2
	ISCED 5 and 6	298.8	284.8	268.6	253.8	291.8
	Total	282.1	256.5	245.6	234.4	261.2

Source: Working population between 25 and 65 years old in PIAAC microdata (OECD 2012)

In the previous Table, we should highlight the skills levels among people in ISCED 1 and in ISCED 2, 3 or 4, as the differences due to social origin are greater there. Therefore, the lower the level of education, the more relevant social origin becomes in skills achieved in adult life. This means that the lower the levels of education, the less social origin differences are compensated. The selective process in education equals the skills from "above" (the differences in university graduates between high and low social origin are 12.5 points) but not from "below" (21.5 point difference in the lowest educational level). For this reason, an increasing number of authors are insisting on the benefits of early schooling to improve both equal opportunities and average skills levels throughout the population (Heckman 2006).

Discussion

Analysis of the data presented leads to the conclusion that it is difficult to find a consistent pattern among the over-qualification indicators and the different individual characteristics since in only one of them is the relationship consistent in all types of over-qualification: years of experience in the job, following the Matching Theory. This lack of consistency might be due to methodological questions or more substantive issues. From the methodological point of view, the sample is considerably reduced when we focus on sub-population according to level of studies and social origin. On the other hand, difficulties are experienced when operationalizing variations of the educational qualifications as they vary widely. In addition, the different over-qualification measurements might be subject to measurement errors, such as grouping the occupation into two digits (due to sampling limits), which might lead us to group together jobs under the same rubric with very different cognitive loads.

From a more substantive point of view, the different studies bring in varying results for each type of over-qualification indicator which might indicate that each type of measurement compiles independent dimensions of the problem and therefore, it is necessary to take a more varied approach. The limitations and possibilities of each type of measurement are given in detail in the introduction.

From the social mobility perspective, we can detect that the higher the father's level of studies, the lower the probability of being overqualified in the objective and subjective indicators but no relationship can be seen in statistical over-qualification for years of schooling. Over-qualification by skills does show a relationship with social origin, although the opposite of what was predicted. The study carried out from the social mobility approach shows that this could be due to greater under-qualification among persons from a high social origin. As they do not have the right educational qualification, their skills are not recognised in the job market.

From the social mobility approach, a strong relationship can be seen between social origin and educational achievement, as usual in this type of studies. However, once a university qualification has been obtained, social origin does not have a major effect on the probability of attaining low qualification jobs. This result is congruent with Boudon's theory (1983), developed more recently by Goldthorpe (2010). According to this theory, we can distinguish two types of mechanisms to explain educational achievement. On the one hand, the "primary effects" that would be all factors that contribute to determining individual capabilities associated with success at school. Among the primary effects there are as many individual factors (health, cognitive capabilities and non-cognitive innate capabilities) as social factors (socioeconomic and cultural level of the family). These effects can be felt in the early stages of the educational system, where some children stand out from others due to their aptitude for good educational performance. However, due to the selection that takes place at the end of each educational stage, the higher the stage, the lower the weighting of the primary effects, as students equal out in performance. For this reason, the differences in skills per social origin are small at the same educational level (Table 5.14), although they are considerable when considering the probability of reaching a particular level of education (Table 5.15).

This data points therefore to the fact that the greatest factor in explaining social inequality is in the relationship between family and educational achievement and to a much lesser extent in the relationship between the educational system and the job market. The data does not support Bourdieu's theses (1991) or Goldthorpe's most recent theses (in the work mentioned with Bukodi), according to which non-cognitive factors play an important role in social mobility. Both authors refer particularly to a context where upper education has become considerably more widespread. To control this fact, estimations were made only for people between 30 and 45 years old, known as the "university boom" in Spain, but the conclusions were no different. Even the very opposite of what both authors propose might happen as persons from low social origin with a university qualification demonstrate that they hold jobs with a large non-cognitive factor load. One hypothesis to be explored is that as opposed to other countries, university expansion has come later and faster in Spain so the historical context cannot be compared with France and the United Kingdom.

CONCLUSIONS

The scope of this study has been the relationship between over-qualification and social mobility aiming to contrast whether social origin might be related to over-qualification and to what extent its relationship might be more or less important than other factors associated with over-qualification, such as gender, age, nationality or work experience. To do this, three common indicators used in the literature on this matter were adapted to the PIAAC data, and two more were added, thanks to the wealth of information in this study. The research focussed particularly on the case of over-qualification of university graduates.

The relationship between the different over-qualification indicators and the characteristics that were studied for workers is not consistent, meaning that the same characteristic might be associated in opposite directions in different indicators. This might be due to both methodological and more substantive problems in the sense that each indicator reflects a different dimension of the problem being studied.

A different approach was tested for over-qualification, working from grouping occupations into four divisions (qualified, semi-qualified white-collar, semi-qualified blue-collar and basic) which methodologically takes us away from the standard over-qualification studies and brings us closer to the tradition of research on social mobility. After witnessing the intense relationship between social origin (measured by the father's level of studies) and the interviewee's level of education, another weaker relationship was revealed: among university graduates, people from a high social origin are more likely to hold qualified jobs. It also happens that the reading skills level of people from a higher social origin is slightly higher, which could explain better job matching for university graduates, partly due to the fact that more of them have degrees rather than diplomas and that their reading skills level is 10 points higher than the rest.

These results suggest that the greater weight of inequality of opportunities lies in the relationship between social origin and educational performance and not so much in the relationship between social origin and the job market. Improving equal opportunities, therefore, should rely more on educational policies than work policies.

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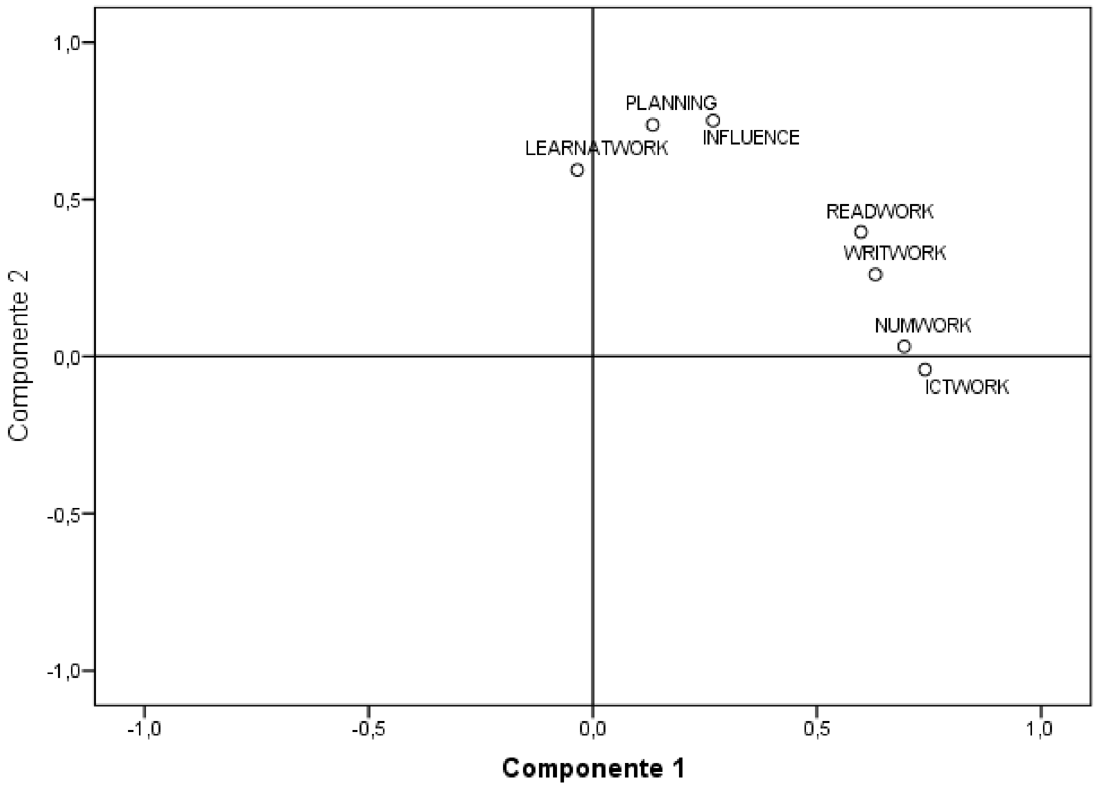
APPENDIX

Graph 5.1. Component plot in rotated space of extracted factors per main component



Calculated only for anyone working and receiving a salary in the week before the survey. Lost cases were replaced by average values.

6. Education, Knowledge and Occupational Profiles

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6. EDUCATION, KNOWLEDGE AND OCCUPATIONAL PROFILES

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ABSTRACT

This study analyzes the results of PIAAC from the perspective of human capital and its aim is twofold. Our first objective is to find out whether education is all that matters in human capital or whether there are other relevant factors. Secondly, we explore to what extent selection procedures based on educational credentials influence the skill levels reached by employed workers who are recruited on the basis of different criteria. This question is explored by comparing the scores of different groups of employed workers in which the importance of educational credentials for employment is higher, e.g. for public employees, who undergo very standardized selection procedures, or lower, such as the self-employed workers or the entrepreneurs, who do not pass selection procedures based on these credentials as they are self-employed. We note the existence of productive environments, such as sectors or firms, more favorable to human capital. Furthermore, the results indicate that by taking into account the educational levels completed in the recruitment process, with all the relevant nuances, we achieve a good predictor of the literacy and numeracy skills of the employed persons, with everything else being constant. The role of educational credentials is also important in the case of business owners. When their levels of education are low their average skill levels will also probably be low. Though in the case of managers the skill levels are substantially higher than those of business owners with or without employees.

Keywords

Human capital, PIAAC, education, skills, public sector, entrepreneurs.

INTRODUCTION

This study analyzes the first results provided by the OECD Programme for the International Assessment of Adult Competences (PIAAC) on the levels of literacy skills (PIAAC-L index) and numeracy skills (PIAAC-M index) of Spanish employed workers. After describing the information, we analyze the determinants of the skill levels reached by individuals by looking at their socio-demographic, education and occupational characteristics. Within the latter two types of factors will be distinguished: those related to the productive environment (firm size and activity sector) and those corresponding to the type of occupation (worker from the public or private sector, manager and entrepreneur with or without employees).

The analysis looks at the PIAAC results from the perspective of human capital and its aim is twofold. On the one hand, we want to know to what extent education is important in human capital: in particular, whether in order to achieve the skill levels that allow respondents to answer the different questions raised by PIAAC there are other relevant factors, either personal or those related to work experience. Secondly, we explore to what extent the selection procedures based on educational credentials influence the skill levels reached by the employed workers who can be differentiated according to the criteria used in their recruitment. This question will be analyzed by comparing the PIAAC scores achieved by the groups of employed persons in which the importance of educational credentials for accessing employment is higher, such as public employees, who undergo very standardized selection procedures, or lower, such as the self-employed or entrepreneurs, who do not pass selection procedures based on these credentials since they are self-employed.

The PIAAC results are useful for addressing these issues. As we shall see, the scores obtained by the employed in literacy and numeracy skills confirm that Spain is characterized by a majority employment of human resources with average qualifications and a limited use of highly qualified human resources. Based on this information, we seek to answer the four following questions:

- Is the educational level of the employed a determining factor for the PIAAC scores obtained by them?
- Are there any factors other than educational ones that might be relevant for the explanation of the numeracy and literacy levels achieved by the employed? Are these factors linked to the characteristics of their work environment?
- Does the different importance attributed to educational credentials in the selection procedures of private and public employees influence their level of human capital, measured according to the PIAAC indices?
- Do entrepreneurs, who are self-selected, have human capital advantages that are reflected in their numeracy and literacy skills and could be associated to their specific characteristics, thus making educational capital less relevant in their case? Do managers, who are selected in markets where educational credentials do matter, also have these advantages?

Following this introduction, the study is structured into four sections. Section 2 briefly contextualizes the study with respect to the related literature and the possibilities of addressing new issues from the PIAAC survey. Section 3 presents the PIAAC indices corresponding to the whole of the Spanish employed population and the different sub-groups considered, their average scores and their structure by levels, as well as their relation to the educational characteristics of the population (levels of education) and the productive fabric (firm size and sectors of activity). Section 4 analyzes the determinants of the individual scores reached in PIAAC, simultaneously considering the role of demographic (gender, age), educational (levels of education), employment (employee, employer) and productive environment (firm size, sector) characteristics. Finally, the main conclusions are summarized.

THE LITERATURE ON HUMAN CAPITAL AND THE RELEVANCE OF PIAAC

PIAAC provides relevant information for improving the analysis of human capital of the employed in several directions: using more complete indicators of human capital than those based only on educational variables; advancing in the analysis of the mismatches between training and job requirements; analyzing the role of educational credentials in the assessment of the productive potential of individuals; assessing the existence of idiosyncratic abilities among entrepreneurs and managers that could reduce, or not, the association between education and skill levels.

PIAAC scores as human capital indicators

The theoretical literature on human capital has pointed out, ever since its beginnings (Schultz, 1962; Becker 1964; Mincer, 1974) that the ability to generate productive services from individuals depends on personal and training factors as well as other factors based on experience, particularly work experience. However, due to the limited availability of information, the heuristics[1] of the role played by human capital in the differences observed in relevant variables such as per capita income, productivity or wages is almost always based on the assessment of the effect of the educational levels of the employed (Mas, Pérez, Uriel, Serrano, 1995). However, it is obvious that the years of schooling and the educational levels completed constitute an approximation of the acquired knowledge and skills, since these indicators ignore the differences in the educational progress among the individuals who complete each level of education. They also ignore the human capital provided by other elements, such as the social or work environment, which are potentially very relevant for learning as shown by assessments of human capital based on wages (Pastor and Serrano, 2002).

1 On the heuristics of availability, ie: the importance of the available information when putting forward interpretations or explanations of the analyzed problems, see Dahneman (2013), chapter 12 (page 174).

The scores in literacy and numeracy provide measurements of the individuals' abilities when answering the PIAAC questionnaire that can be interpreted as a result of the accumulation of several different types of human capital, not just educational. PIAAC analyzes two important dimensions of the skills and abilities of individuals for their occupational performance, literacy and numeracy, assessing them in a way which allows us to explore the effect on them of the factors that influence human capital and are rarely quantified. Thanks to the extensive information provided on the respondents, PIAAC allows us to analyze the relationship between the scores obtained in the two skills assessed and the numerous demographic, educational, work and psychosocial characteristics of the individuals.

Mismatch between skills and job requirements

A common trait of today's job market is the need for lifelong learning and the acquisition of skills inside and outside the education system. Technological advances, particularly the growing presence of information and communication technologies (ICT), are changing the specific requirements of many jobs very quickly and force workers to update their skills in order to adapt to these changes (Rouet et al, 2009). In this sense, a sufficient level in skills that facilitate learning, especially literacy and numeracy, is essential for keeping a job in modern societies.

Furthermore, the economies of these advanced societies demand from a growing percentage of workers and especially those who direct them, higher cognitive skills related to the understanding, interpretation, analysis and communication of ever more complex information (Gal et al, 2009). As a result, the employed must face adaptation challenges and adjust to the job requirements more often.

Assessing the occupational mismatch requires measuring the skills of individuals in every moment of their working lives and also the requirements of the available jobs at that moment. PIAAC is an important step in assessing this problem by providing measurements of the current distribution of skills. PIAAC pursues two objectives related to the assessment of the mismatch: to measure the differences in basic skills both within and among countries, and to assess the relationship between the skills of adults and the different economic and social features, such as productive specialization, income, the characteristics of the job, the educational level reached, participation in lifelong learning, health, social capital, etc. (Gal et al, 2009).

Educational credentials and skill levels

The role of educational credentials in the job market may be very different depending on the groups of employed. The selection processes are different among sectors and depend on the size of the firms, but they are particularly different among some groups of the employed. For example, among the salaried employees the processes are clearly different between the public and private sectors, since in the public sector being subject to regulated procedures is much more common. Consequently, theoretically objective indicators such as educational credentials play a major role in the case of public employees. On the other hand, within the private sector there is a clear difference between the selection procedures of salaried employees (which are selected according to market-based criteria and indicators, usually including educational levels and other ability tests) and those of entrepreneurs with or without salaried employees, who by definition are self-employed and do not have to pass such selection processes.

It is known that the educational characteristics of those employed in the various activity sectors of the public and private sectors are very different and that, in general, the concentration of employees with high educational levels in the public sector is greater (Alba-Ramírez and San Segundo, 1995 , García et al, 1997; Lassibille 1998; Peiró et al, 2012). It is also known that in Spain the average educational level of entrepreneurs is low, particularly among the self-employed, while among professional managers it is high (Serrano and Hernández, 2008; Pérez and Serrano, 2013).

By providing skill indicators for the employed, PIAAC offers interesting possibilities for analyzing the role of educational credentials among different groups. Specifically, it allows us to analyze the extent to which a more intensive use of educational indicators in personnel selection provides human resources with higher skill levels.

Specific characteristics of the entrepreneurs and skill levels

In the literature the features that identify entrepreneurs are related to their quality of judgment, which allows them to succeed more in uncertain contexts, and to their skills in different aspects: taking risks (Knight, 1921, Kihlstrom and Laffont, 1979); making the most financially of the available knowledge (Schumpeter, 1934); covering unsatisfied needs (Kirzner, 1973); coordinating economic activity and directing teams according to their own plans within their firms in spite of the overall situation of the market (Coase, 1937); processing and synthesizing information for decision-making, despite the information often being incomplete and sometimes contradictory (Casson, 1982). All these skills (and those of the managers who also perform entrepreneurial tasks) are valuable when facing uncertainty and seem to be linked with factors that have nothing to do with education.

A corollary of the idea that education is not relevant for entrepreneurship is that training is not important for an entrepreneur to achieve sufficient skills. This interpretation is true in Spain, where there is a high percentage of self-employed workers and entrepreneurs with employees who have a low educational level. However, another group of the employed that also carries out entrepreneurial activities is the professional managers who have much higher educational levels (and are selected by means of market criteria). It must be kept in mind that the higher educational levels of decision-makers in firms are associated with more intensive specialization of knowledge and with larger and more competitive firms. Furthermore, the training of entrepreneurs has a positive influence on the intensity with which human capital is used and optimized (Pérez and Serrano, 2013).

PIAAC offers an interesting opportunity regarding this subject: checking whether the skill levels of literacy and numeracy in the case of entrepreneurs are associated with their educational levels in a different way than in the case of managers or other groups of employed. With the help of the PIAAC results we can check whether entrepreneurs reach higher skill levels than those which would correspond to their other characteristics or if, on the contrary, they do not show significant differences.

THE SKILLS OF THE SPANISH EMPLOYED, ACCORDING TO PIAAC

This section describes the skill levels reached by the Spanish employed, classifying them into groups that will be used for the following analysis of the determinants that will be focused on answering the questions outlined in the introduction.

Average levels

The average skill levels in literacy (PIAAC-L) and numeracy (PIAAC-M) of the Spanish employed are average-to-low, both from the perspective of their scores (between 256 and 260 points on a scale of 500) and from the most frequent level perspective (level 2, third in the <1-5 scale considered). 70-72% of the respondents are at level 2, which means they are able to perform low level inferences, do calculations and interpret relatively simple data; and level 3, which requires the individual to be able to deal with texts and solve problems with more complex information. Only 6% reach levels 4 or 5, which require higher skills in the management and interpretation of information regarding texts, statistics, probabilities, formulas or mathematical representations.

In general, the results of the Spanish employed are slightly lower in numeracy than in literacy, although the differences turn out to be modest on average. In contrast, entrepreneurs show in this aspect a different behaviour to the general one: entrepreneurs, with or without employees, reach the same level in both dimensions and managers[2] achieve a higher PIAAC-M index than PIAAC-L. On the other hand, among public employees the superiority of PIAAC-L with respect to PIAAC-M is greater than in the other categories of the employed.

Two groups of employees that we are going to analyze stand out from the group because of their average skill levels in the analyzed fields: public employees and, specially, professional managers.[3] Public employees have higher literacy levels, but the structure of the levels of both PIAAC indices is similar to the average. Managers stand out in both indices, which are at level 3, especially in their numeracy skills. According to PIAAC, a vast majority of professionals who

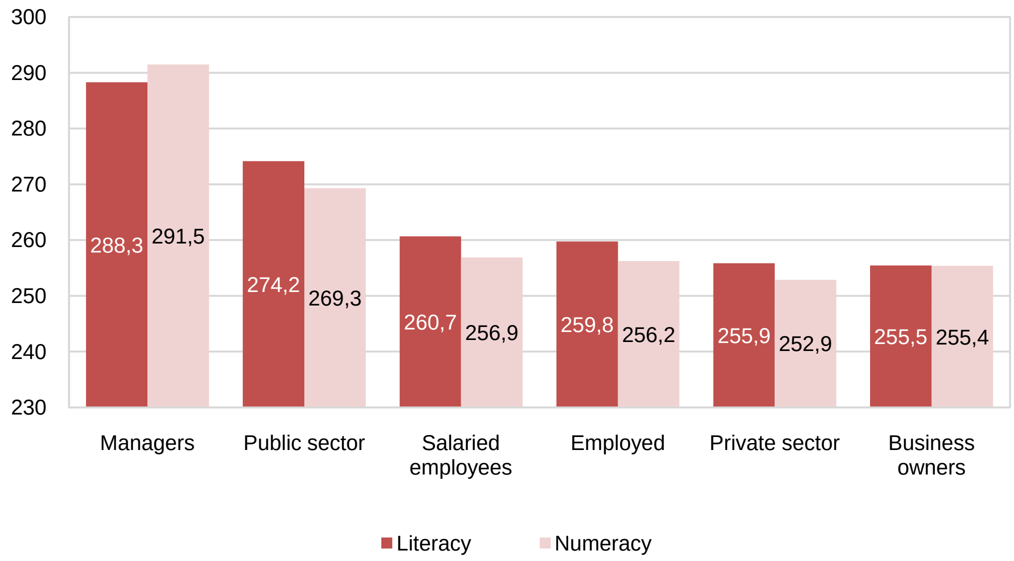
[2] The sample of managers in the PIAAC survey is limited, but the analyzed results are consistent with previous studies on this group of workers.

[3] We have to keep in mind that some of the relationships analyzed in this study are endogenous, in the sense that we cannot distinguish whether managers or public employees reach higher skill levels during the performance of their tasks, or whether they already had them from the beginning and because of that have become managers or public employees. Also, in general, the greater the innate abilities the easier it will be to achieve higher education levels and, at the same time, given the abilities, the higher the level reached in the education system the higher the probability will be of increasing the skills (Hernandez and Serrano, 2013).

perform managerial tasks, over 60%, reach levels 3 and 4 of the scale, so that, in their case, we can talk about medium to high levels of human capital.

There is a sharp contrast between managers and entrepreneurs, both in their average scores of the two PIAAC skills as well as in their structure of levels. The percentage of entrepreneurs who reach at least level 3 is only a third (35% in literacy and 33.2% in numeracy) while managers almost double this percentage (64.3% and 68.2%, respectively). In contrast, there are no significant differences between the entrepreneurs with respect to the average of the employed, private sector employees or the whole group of salaried employees.

Graph 6.1. PIAAC score in literacy and numeracy of the employed, salaried employees, business owners, managers and public and private sector workers



Average of the 10 plausible PIAAC values. Source: PIAAC and authors' calculations.

Table 6.1. Percentage structure of the PIAAC performance levels in literacy and numeracy of the employed, employees, business owners, managers, and workers in the private and public sectors

	Literacy						Numeracy					
	N<1	N1	N2	N3	N4	N5	N<1	N1	N2	N3	N4	N5
Employed	4.2	17.2	38.9	33.0	6.4	0.3	5.8	17.8	39.5	30.9	5.9	0.1
Salaried employees	4.1	16.8	38.4	33.8	6.7	0.2	5.9	17.7	38.5	31.7	6.0	0.1
Business owners	4.7	19.9	40.5	29.7	4.7	0.6	5.2	18.3	43.3	27.3	5.9	-
Managers	-	7.9	27.8	45.4	16.8	2.1	-	6.6	25.2	45.0	23.2	-
Public sector	4.9	18.6	40.7	30.4	5.3	0.2	6.7	19.8	39.7	28.1	5.8	-
Private sector	1.6	12.5	32.8	42.4	10.1	0.6	2.7	10.3	39.0	41.2	6.6	0.2

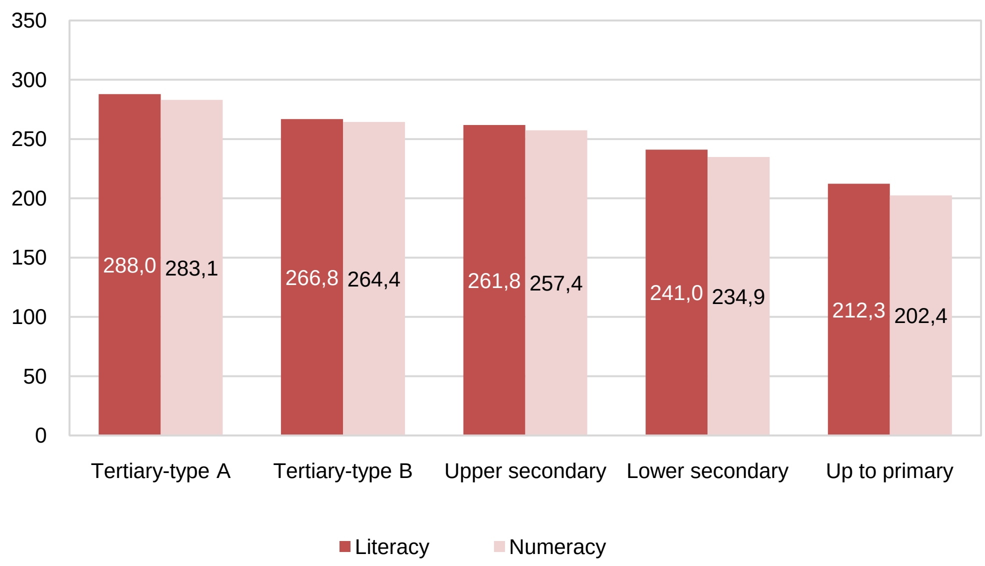
Levels PIAAC: <1 (less than 176 points), 1 (176-225 points), 2 (226-275 points), 3 (276-325 points), 4 (326-375 points), 5 (376-500 points).
Source: PIAAC y own preparation.

PIAAC levels vs levels of education

PIAAC indices can be interpreted as alternative indicators of human capital, instead of the usual indicators based on educational levels, since they measure the ability to perform the skills considered in the survey. From this perspective, it is relevant to explore the relationships between PIAAC-L and PIAAC-M and the information on the educational characteristics of the employed provided by the survey.

The first finding is that PIAAC scores increase on average with the level of education. The average of those who have primary education is situated at level 1 of PIAAC while the averages of the following three educational stages, i.e. lower secondary, upper secondary and tertiary-type B (CFGS and FPII, Spain's professional training programmes) education, are situated at level 2. The employed with university education (tertiary-type A) are situated, on average, at level 3, although it should be noted that the average score for this group is 288 for PIAAC-L and 283 for PIAAC-M, closer to the minimum value of this level's range (275-325) than to the lowest value of level 4 (325).

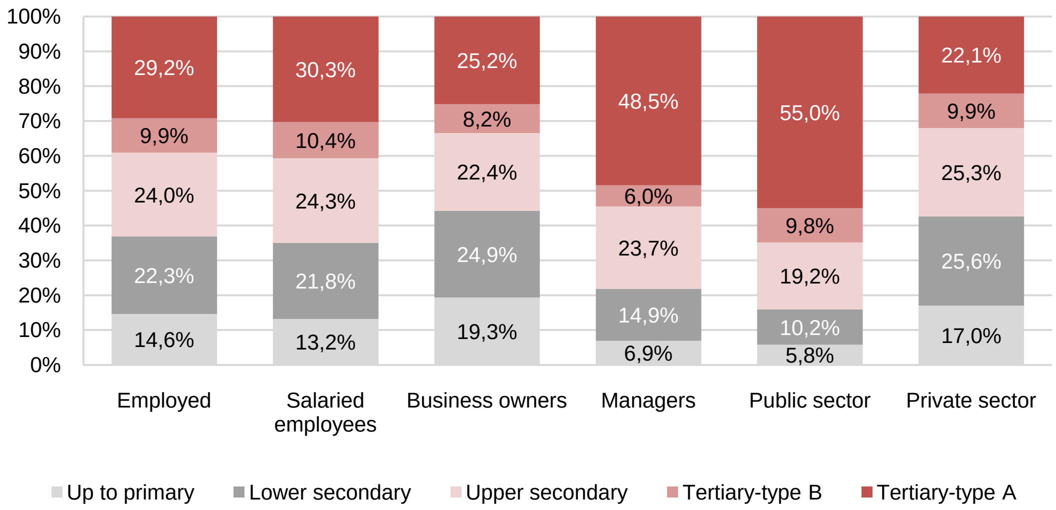
Graph 6.2. PIAAC scores in literacy and numeracy of the employed by levels of education



Average of the 10 PIAAC plausible values. Source: PIAAC and authors' calculations.

The structure by educational levels of the different categories of employed that we have considered shows high percentages of tertiary education graduates among the public employees (64.8%) and the managers (54.5%). By contrast, only 34% of entrepreneurs reach this level of education.

Graph 6.3. Structure by educational levels of the employed, salaried employees, entrepreneurs, managers, and public and private sector workers



Source: PIAAC and authors' calculations.

Table 6.2. Structure by PIAAC levels of the employed and salaried employees in each educational level

Literacy	Employed					Salaried employees				
	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary-type B	Tertiary-type A	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary-type B	Tertiary-type A
Level <1	14.6	5.4	2.4	0.4	0.8	16.2	5.1	2.3	0.3	0.7
Level 1	32.1	27.1	16.7	13.5	3.9	30.2	27.5	17.1	13.8	4.0
Level 2	42.5	45.9	44.4	39.6	27.9	42.5	45.4	43.0	39.2	28.4
Level 3	10.6	20.6	32.8	42.0	50.2	10.7	21.3	33.9	42.0	49.3
Level 4	0.3	1.0	3.6	4.6	16.5	0.4	0.7	3.7	4.7	17.1
Level 5	-	-	0.1	-	0.8	-	-	-	-	0.6
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

Numeracy	Employed					Salaried employees				
	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary -type B	Tertiary-type A	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary-type B	Tertiary-type A
Level <1	18.5	9.2	3.2	1.1	0.6	20.1	9.7	3.0	1.0	0.7
Level 1	34.3	26.3	17.5	13.1	5.1	34.8	26.5	17.3	14.8	5.6
Level 2	37.8	46.0	43.6	45.3	30.1	36.6	44.8	43.2	43.9	29.3
Level 3	9.1	17.4	30.9	34.8	50.6	8.1	17.5	31.5	35.9	50.9
Level 4	0.3	1.2	4.8	5.7	13.3	0.4	1.4	5.0	4.4	13.2
Level 5	-	-	-	-	0.2	-	-	-	-	0.3
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

PIAAC level: <1 (less than 176 points), 1 (176-225 points), 2 (226-275 points), 3 (276-325 points), 4 (326-375 points), 5 (376-500 points).
Source: PIAAC and authors' calculations.

Table 6.3. Structure by PIAAC levels of the entrepreneurs and managers in each educational level

Literacy	Entrepreneurs					Managers				
	Up to primary	Lower secon-dary	Upper secon -dary	Tertiary-type B	Tertiary-type A	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary-type B	Tertiary-type A
Level <1	12.9	5.9	1.3	16.2	1.2	-	-	-	-	-
Level 1	36.8	27.7	18.5	30.2	3.0	-	20.3	13.7	36.1	4.0
Level 2	39.0	45.3	52.6	42.5	26.2	-	30.2	41.0	42.4	24.1
Level 3	11.3	18.2	27.0	10.7	53.5	-	49.5	35.3	21.5	48.5
Level 4	-	2.8	0.6	0.4	13.7	-	-	10.0	-	20.6
Level 5	-	-	-	-	2.3	-	-	-	-	2.8
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**-**	**100.0**	**100.0**	**100.0**	**100.0**

Numeracy	Entrepreneurs					Managers				
	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary -type B	Tertiary-type A	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary-type B	Tertiary -type A
Level <1	15.3	5.7	2.4	20.1	0.4	-	-	-	-	-
Level 1	33.6	25.1	20.2	34.8	2.8	-	20.3	-	36.1	5.0
Level 2	36.9	51.8	48.1	36.6	32.3	-	61.9	46.9	42.4	16.5
Level 3	14.1	16.9	26.6	8.1	48.5	-	17.8	37.8	21.5	50.3
Level 4	-	0.5	2.8	0.4	15.9	-	-	15.3	-	28.2
Level 5	-	-	-	-	-	-	-	-	-	-
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**-**	**100.0**	**100.0**	**100.0**	**100.0**

PIAAC levels: <1 (less than 176 points), 1 (176-225 points), 2 (226-275 points), 3 (276-325 points), 4 (326-375 points), 5 (376-500 points).
Source: PIAAC and authors' calculations.

Table 6.4. Structure by PIAAC levels of the employed in the public sector and private sector in each educational level

Literacy	Private sector					Public sector				
	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary -type B	Tertiary-type A	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary -type B	Tertiary -type A
Level <1	14.8	5.8	2.3	0.5	1.0	14.0	2.0	2.0	-	0.5
Level 1	31.8	26.9	15.9	13.8	3.9	30.1	33.9	20.9	10.9	4.0
Level 2	43.3	45.6	46.3	38.3	28.2	37.9	43.1	35.7	46.3	27.2
Level 3	9.9	20.5	31.5	42.5	50.5	18.0	21.0	39.7	40.6	49.9
Level 4	0.3	1.2	3.9	4.9	15.8	-	-	1.8	2.2	17.3
Level 5	-	-	0.1	-	0.6	-	-	-	-	1.0
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

Numeracy	Private sector					Public sector				
	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary-type B	Tertiary-type A	Up to primary	Lower secon-dary	Upper secon-dary	Tertiary-type B	Tertiary-type A
Level <1	18.9	9.5	2.9	1.0	0.8	16.4	6.1	3.7	1.8	0.4
Level 1	33.9	26.8	18.4	12.7	5.4	38.5	19.2	11.9	12.4	4.9
Level 2	37.9	45.1	43.3	43.6	29.0	33.4	54.6	45.8	54.8	31.3
Level 3	9.0	17.3	30.2	36.4	49.2	11.8	20.1	35.5	27.4	52.7
Level 4	0.3	1.3	5.2	6.4	15.5	-	-	3.1	3.6	10.2
Level 5	-	-	-	-	0.1	-	-	-	-	0.4
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

PIAAC levels: <1 (less than 176 points), 1 (176-225 points), 2 (226-275 points), 3 (276-325 points), 4 (326-375 points), 5 (376-500 points).
Source: PIAAC and authors' calculations.

Inside each educational level the range of the values of the PIAAC scores is quite considerable —for primary education there are maximum individual scores close to 341 points and minimum scores of around 98— but these extreme values are not representative for the general trend. In the general trend the structure of educational levels is positively associated with the PIAAC indices structure of levels, as shown in Tables 6.2 to 6.4. While PIAAC levels <1 and 1 predominate among those with the lowest educational levels, those with secondary education usually obtain level 2, and level 3 gains in importance. Level 3 is the most common among those who have higher education. Thus we can state that reaching literacy and numeracy levels equal to or higher than 3 without having higher education is rare, while two out of three university graduates reach those medium-high levels.

One aspect that we will look at in different ways is whether the conditionality associated with these levels of education in order to achieve high skill levels also applies in the case of entrepreneurs, particularly in the case of business owners with or without salaried employees. It is known that the latter have, on average, medium educational levels similar to those of the whole employed group and clearly lower than those of professional managers. However this fact may be related to two different types of factors: first, to the fact that firm owners do not have to undergo selection processes in a job market where educational credentials play a role; and secondly, it could be that formal education is not necessary for them to acquire skills.

This second hypothesis can be checked in the light of the data provided by the PIAAC scores, by looking at the literacy and numeracy skills of the entrepreneurs, which are without doubt relevant to the performance of managerial functions. In view of the data, entrepreneurs are not different in this regard and, although there are exceptional cases: it is rare to find examples of entrepreneurs with low levels of education and high levels of skills. In fact there are hardly any entrepreneurs who reach high levels (4 and 5) of PIAAC-L and PIAAC-M skills, except among those who are university graduates. Among the managers with upper secondary and university education there is a high percentage of individuals with high skill levels. On the other hand, entrepreneurs without tertiary-type A education very often do not reach level 2 of PIAAC.

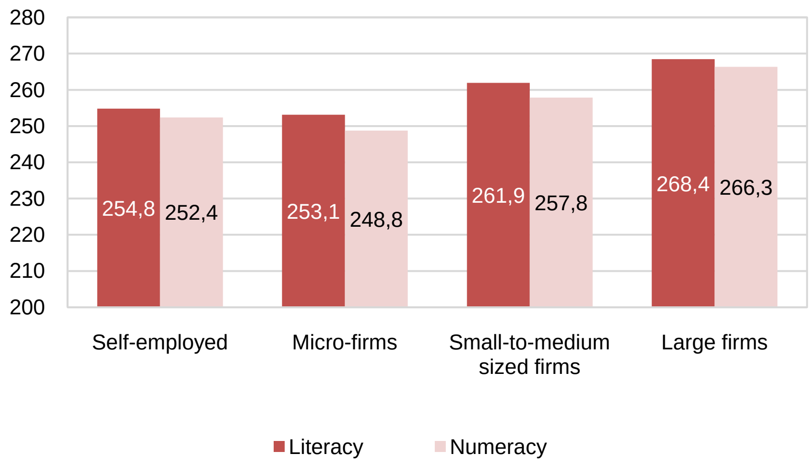
The contrast observed between the educational levels of the two categories of entrepreneurs that we distinguish, business owners and managers, conditions, therefore, the average skill levels of both. Something similar happens, but in a less pronounced way, between the workers of the public and private sector. Although traditionally the public sector has a large percentage of highly qualified employees, in the last two decades the private sector and, in particular, the sales-based services have become a major source of employment for those with high qualifications, especially university graduates. In both sectors employed workers with medium-to-high levels of literacy and numeracy skills (levels 3, 4 or 5) are common among individuals with tertiary education. The percentage is higher in the public sector than in the private sector, but also in the latter case it is already high.

PIAAC levels of the employed vs productive environment

Another aspect which is interesting to analyze is the influence of the characteristics of the productive fabric on the average levels of the PIAAC scores of the employed. It is particularly interesting to analyze the relationship between PIAAC-L and PIAAC-M of the employed and the size of the company or the sector of activity in which they work.

As for the size of the firm, the larger it is the higher the average level of their workers' PIAAC scores. The level corresponding to the micro-firms (less than ten employees) is the lowest and similar to that of the self-employed, while the highest is that of large firms. However, the differences are not substantial (between 12 and 14 index points) and the average values of all company sizes are at level 2.

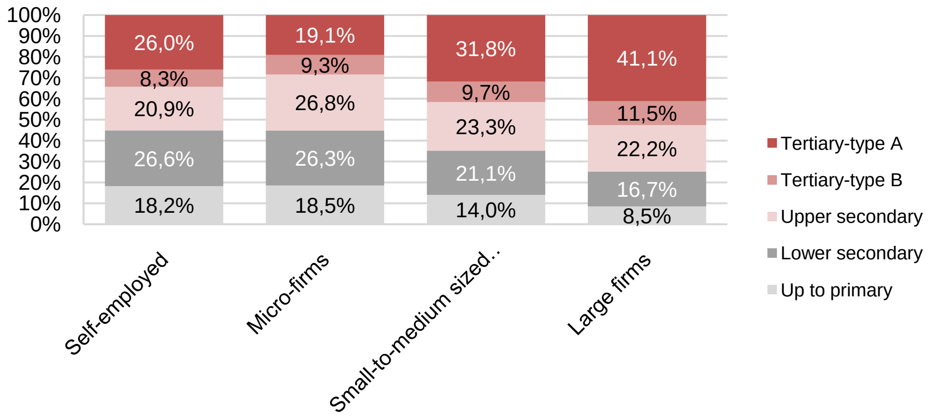
Graph 6.4. PIAAC scores of the employed, by firm size



Average of the 10 PIAAC plausible values.
Small firms: from 1 to 10 salaried employees, Small and medium size firms: from 11 to 50 salaried employees, Big firms: more than 50 salaried employees.
Source: PIAAC and authors' calculations.

These data match the scope of other information already known: that in many countries, and certainly in Spain, the structure by educational levels of the employed of firms of different sizes is very diverse. While among the self-employed and micro-firms 45% of their workers have lower secondary education at most and only a third have tertiary education, in large firms the majority have higher education and 25% are individuals with up to lower secondary education.

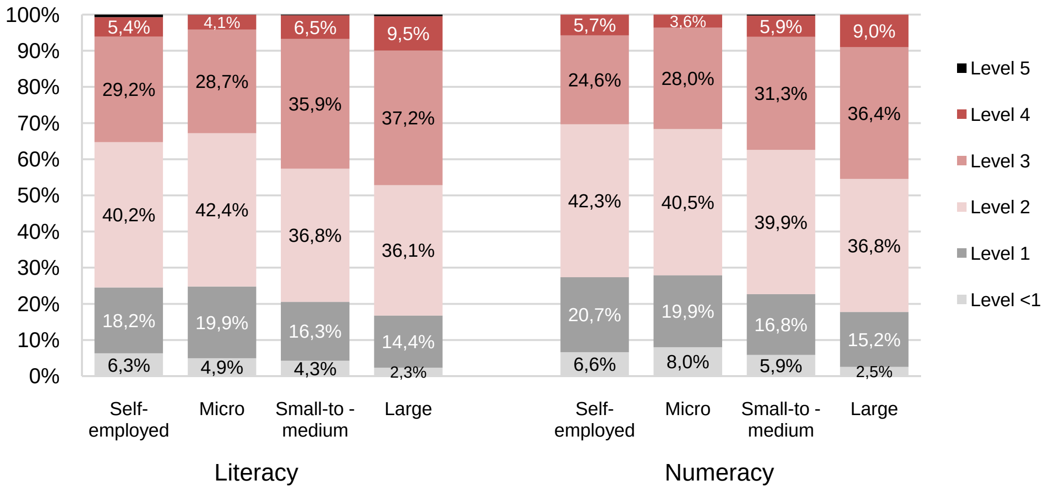
Graph 6.5. Structure by educational level of the employed, by firm size



Small firms: from 1 to 10 salaried employees, Small and medium size firms: from 11 to 50 salaried employees, Big firms: more than 50 salaried employees.
Source: PIAAC and authors' calculations..

The results provided by Graph 6.6 show that the differences in the structure by educational levels have a limited effect on the PIAAC levels structure based on the different sizes of firm. In all cases the percentages of the employed who reach the highest levels of this index (4 and 5) are low and the medium levels (2 and 3) predominate overwhelmingly, representing about two thirds of the personnel.

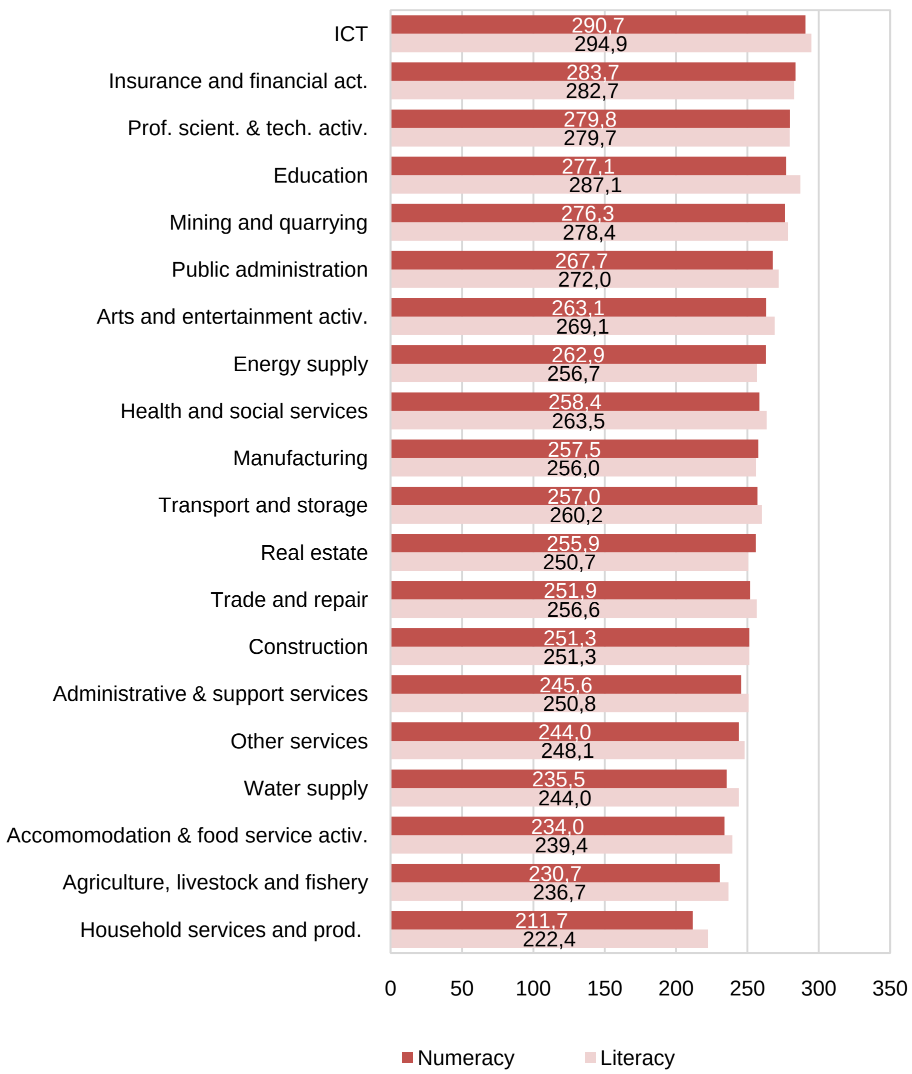
Graph 6.6. Structure by PIAAC levels of the employed by different firm sizes



PIAAC levels: <1 (less than 176 points), 1 (176-225 points), 2 (226-275 points), 3 (276-325 points), 4 (326-375 points), 5 (376-500 points).
Source: PIAAC authors' calculations.

On the other hand, the average PIAAC scores of the employed in the different sectors show more substantial differences. However, it is advisable to take these data with caution, since the PIAAC sample is not representative of the sector of activity. The disaggregation into twenty sectors exposed in Graph 6.7, shows that the average values of the PIAAC indices differ by up to 79 points. They can be divided into three groups of activities. First, in five sectors the average values are over 275 points and are situated at level 3 of the index: ICT; financial and insurance activities; professional, scientific and technical service activities; education; and mining and quarrying. Those employed in these activities enjoy a work environment made up of people with higher skill levels. Secondly, a large group of fourteen sectors reaches average scores corresponding to level 2 of PIAAC, higher than 250 points but lower than 275.[4] At the top of this group are public administration, arts and entertainment activities, energy supply activities and health and social activities; in the middle are the manufacturing industries, transport, real estate activities, trade and construction; in the lowest part of this second group are the accommodation and food service activities. In the third group, which is far away from the other two and has an average index value that classifies it at level 1 of PIAAC, we find the household services, which have the work environment with the lowest level of skills.

Graph 6.7. Average PIAAC scores of the employed by sector of activity



Average of the 10 PIAAC plausible values. Source: PIAAC and authors' calculations.

[4] In this disaggregation the Public Administration sector does not include the public employees from the health and education sectors, which are considered as separate activities.

DETERMINANTS OF THE DIFFERENCES IN THE PIAAC SCORES OF EMPLOYED WORKERS

The description in the previous section of the average PIAAC scores of the employed workers and the different subgroups considered, as well as the information on the structures of levels and the influence of the educational characteristics or the productive environment in which they work, points to the fact that educational levels do have an effect on the skill levels. At the same time, we note that some characteristics of the productive fabric, such as the firm size and especially the type of activity, also influence them. On the other hand, the differences observed between the PIAAC scores of the public and private sectors employed workers or between business owners and managers indicate that a possible influence of the different human resource selection procedures on the skill levels should not be ruled out.

This section analyzes the influence of all of these factors by means of a statistical analysis of the determinants of the differences in the PIAAC-L and PIAAC-M indices of employed workers. We carry out a regression analysis using ordinary least squares (OLS), which estimates the average population value of the dependent variable in terms of the known or fixed values of the explanatory variables. In the constructed models the dependent variable is the PIAAC score obtained in literacy or numeracy[5]. For each one three different estimations are carried out with the aim of analyzing the score differences associated with individuals belonging to the different groups: (1) private sector vs. public sector employees; (2) business owners vs. managers; (3) salaried employees vs. business owners.

The sequence of exercises shown allows us to analyze the effect of the demographic characteristics on the PIAAC scores in the literacy or numeracy skills (Table 6.5), the changes that occur when educational characteristics are added to these variables (Table 6.6) or, alternatively, the characteristics of the firms and of the sectors of activity where individuals are employed (Table 6.7). Finally, we analyze the joint effect of all of the demographic, educational and productive variables considered (Table 6.8).

Effect of the demographic characteristics on the PIAAC scores

The regressions presented in Table 6.5 analyze the effects of three types of demographic variables: gender, nationality and age group. The results indicate that being a woman has a penalty effect on the PIAAC score of between 6 and 8 points in literacy and between 13 in and 17.6 in numeracy, all else being equal. Being a foreigner has a penalty effect of between 22 and 28 points, although belonging to this group is not significant when the dummy of being an entrepreneur is taken into account and also, therefore, for the subsample of business owners (columns 2 and 5).

[5] The econometric analyses are based on the first plausible value of the numeracy and literacy test.

As for the influence of the respondents' age , there are no significant differences among the groups up to the age of 44, but from the age group of 45-55 years onwards and, especially, among the participants of more than 54 years, negative and significant differences are observed with respect to the reference group (16 to 24 years). Taking into account the dummy of belonging to the public or private sector (columns 1 and 4), those over the age of 54 years get on average 29 points less in literacy and 28 points less in numeracy.

In columns 1 and 4 we have included a dummy to classify workers by the type of sector (public or private) in which they are employed. Everything else being constant, being a public employee has a positive significant effect which means getting about 19 points more in literacy and 17.3 in numeracy. A similar analysis for assessing the difference between salaried employees and business owners does not produce significant differences (columns 3 and 6).

In columns 2 and 5 we consider a subsample of the total number of employed in which only entrepreneurs are taken into account. This specification includes a dummy to assess the effect on the PIAAC level of being a business owner instead of being a manager. Everything else being constant, being a business owner, with or without employees, has a negative and significant effect as opposed to being a manager with 29.4 points in literacy and 31.1 points in numeracy.

Table 6.5. OLS regressions of the PIAAC scores in literacy and numeracy, by demographic characteristics

		Dependent variable: Literacy score						Dependent variable: Numeracy score					
		(1)		(2)		(3)		(4)		(5)		(6)	
Ref: Man	Woman	-7.490	***	-8.042	**	-6.020	***	-14.369	***	-17.624	***	-12.928	***
		(1.749)		(3.687)		(1.706)		(1.681)		(3.578)		(1.680)	
Ref: National	Foreigner	-22.109	***	-5.636		-26.451	***	-24.091	***	-6.086		-28.481	***
		(3.097)		(6.041)		(3.170)		(3.173)		(6.457)		(3.180)	
Ref: 16-24 years	25-34 years	6.808	*	-1.016		6.429	*	7.294	**	5.570		6.759	*
		(3.438)		(12.336)		(3.774)		(3.522)		(14.147)		(3.773)	
	35-44 years	3.081		0.065		3.850		5.948	*	3.013		6.355	*
		(3.195)		(10.997)		(3.712)		(3.227)		(12.651)		(3.606)	
	45-54 years	-7.247	**	-4.209		-4.832		-7.687	**	-4.855		-6.060	
		(3.249)		(11.842)		(3.954)		(3.671)		(12.761)		(4.108)	
	55 years and more	-29.358	***	-27.842	**	-27.053	***	-27.941	***	-24.780	*	-27.001	***
		(3.536)		(11.109)		(4.009)		(3.834)		(12.604)		(3.930)	
Ref: Private sector	Public sector	19.128	***					17.254	***				
		(2.003)						(1.985)					
Ref: Manager	Business owner			-29.365	***					-31.108	***		
				(4.965)						(4.231)			
Ref: Business owner	Salaried employee					2.179						-1.900	
						(2.245)						(2.170)	
	Constant	265.405	***	296.128	***	266.549	***	264.252	***	299.174	***	269.056	***
		(3.053)		(12.098)		(4.138)		(3.221)		(13.026)		(3.884)	
	N	3324		630		3261		3324		630		3261	
	R^2	0.116		0.128		0.090		0.125		0.159		0.107	
	F	52.148		11.046		31.683		59.292		17.761		49.707	

***, **, *: significant at 1%, 5% y 10% respectively. Standard errors in parentheses, calculated using the Jackknife2 replicaction procedure for 80 replicated weights.
Source: PIAAC and authors' calculations.

Joint effect of the demographic and educational characteristics on the PIAAC scores

The effect of the demographic variables may be biased because the specifications in Table 6.5 leave out the impact of the educational level reached by the participants. When this is added as an independent variable, differentiating the employed workers also by their level of education completed (five), it turns out to be very significant and the coefficient of determination increases, but at the same time the explanatory power of some variables that were previously significant diminishes.

Table 6.6. OLS regressions of the PIAAC scores in literacy and numeracy, by demographic and educational characteristics

		Dependent Variable: Literacy score			Dependent Variable: Numeracy score		
		(1)	(2)	(3)	(4)	(5)	(6)
Ref: Man	Woman	-11.827 ***	-11.791 ***	-11.373 ***	-18.887 ***	-21.429 ***	-18.421 ***
		(1.561)	(3.264)	(1.543)	(1.455)	(3.093)	(1.472)
Ref: National	Foreigner	-20.199 ***	-4.732	-20.719 ***	-22.252 ***	-5.188	-22.793 ***
		(2.854)	(5.879)	(2.928)	(2.866)	(6.484)	(2.909)
Ref: 16-24 years	25-34 years	-1.862	-14.614	-3.031	-1.579	-8.254	-2.783
		(2.944)	(11.748)	(3.222)	(2.950)	(14.386)	(3.203)
	35-44 years	-3.803	-14.343	-4.730	-0.896	-11.642	-2.121
		(2.784)	(11.114)	(3.165)	(2.870)	(13.574)	(3.182)
	45-54 years	-9.744 ***	-13.096	-10.216 ***	-9.845 ***	-14.170	-11.128 ***
		(2.788)	(11.522)	(3.297)	(3.207)	(13.588)	(3.561)
	55 years and over	-25.205 ***	-27.443 **	-25.893 ***	-22.752 ***	-24.759 *	-24.971 ***
		(3.243)	(11.213)	(3.609)	(3.537)	(13.677)	(3.617)
Ref: Up to primary	Lower secondary	15.580 ***	16.065 ***	16.352 ***	18.644 ***	15.955 ***	18.812 ***
		(2.735)	(5.333)	(2.813)	(2.758)	(4.948)	(2.835)
	Upper secondary	34.853 ***	28.884 ***	34.893 ***	41.226 ***	32.185 ***	40.945 ***
		(2.729)	(5.055)	(2.903)	(3.011)	(5.494)	(3.178)
	Tertiary-type B	37.818 ***	40.323 ***	38.672 ***	45.422 ***	47.272 ***	45.480 ***
		(3.020)	(6.988)	(3.117)	(3.075)	(7.045)	(3.082)
	Tertiary-type A	63.223 ***	62.815 ***	64.503 ***	66.925 ***	62.260 ***	67.279 ***
		(2.802)	(5.237)	(2.850)	(2.892)	(4.503)	(2.913)
Ref: Private sector	Public sector	2.565 *			0.231		
		(1.531)			(1.489)		
Ref: Manager	Business owner		-7.476			-9.952 **	
			(5.018)			(4.940)	
Ref: Business owner	Salaried employee			-0.241			-4.502 **
				(1.871)			(1.784)
	Constant	241.001 ***	254.620 ***	241.648 ***	235.808 ***	257.602 ***	240.664 ***
		(3.745)	(12.978)	(4.560)	(3.734)	(15.195)	(4.195)
	N	3323	630	3260	3323	630	3260
	R^2	0.319	0.334	0.318	0.332	0.352	0.333
	F	111.387	21.237	119.362	90.151	33.379	98.710

***, **, *: significant at 1%, 5% y 10% respectively. Standard errors in parentheses, calculated using the Jackknife2 replicaction procedure for 80 replicated weights.
Source: PIAAC and authors' calculations.

In all of the regression specifications shown in Table 6.6, completing a higher educational level has a positive and significant effect on the PIAAC score. University graduates (tertiary-type A education) get an average of 63 points more in literacy than individuals with up to primary education, which is equivalent to climbing two steps in the PIAAC index levels. The difference is of 47.6 points when compared with individuals with lower secondary education, between 26 and 34 points with participants who have upper secondary education (high school and intermediate vocational training and equivalents), and between 21.5 and 26 points more than individuals with tertiary type-B education. These differences between the university graduates and the rest of the employed workers are slightly lower for the case of the numeracy scores, except for individuals with up to primary education, where the difference increases up to 67 points .

The impact of the educational variables on the contribution of the demographic characteristics (gender, nationality, age) is small, hardly affecting its significance or its coefficients. The permanence of the negative effect of age rules out that it may only be something associated with the educational improvements of the younger generations, and points to the hypothesis of the presence of diminishing returns in the individuals' skills as they approach fifty years of age[6].

In contrast, the dummies of belonging to the different occupational groups considered are affected and, in some cases, are no longer significant when the educational level is taken into account. However, being a business owner as opposed to being a manager does adversely affect the score of the PIAAC-M index and being a salaried worker as opposed to being a business owner also carries a penalty of 4.5 points in numeracy, these two results being significant to 5%.

This loss of significance of the occupational variables indicates that the differences in the associated scores may actually be explained by the different educational levels of the individuals. In other words, the higher skill levels of public employees or managers are due to their higher educational levels and, after taking these into account, the differences between belonging to one group or another are not statistically significant.

Joint effect of the demographic and productive characteristics on the PIAAC scores

In the third set of specifications, the demographic variables are combined with those that can pick up the effect of a different type of human capital other than the educational, associated with the characteristics of the productive fabric in which individuals carry out their jobs, such as the size of the firms and the sector of activity[7]. In view of the results, these types of variables have significant effects in some cases on the value of the indices and the overall significance of the regressions increases, though less than when the educational variables are introduced.

6 In relation to the depreciation of the skills see the papers of Villar (2013) and of Hernández and Serrano (2013) in this volume.

7 Both in this specification and in the following (with demographic, productive and educational variables) exercises have been repeated substituting the age variable with another of work experience and the results are alike, with very similar coefficients, so that the age variable has been maintained in order to simplify the presentation of results.

Table 6.7. OLS regressions of the PIAAC scores in literacy and numeracy by demographic and productive characteristics

		Dependent variable: Literacy score			Dependent variable: Numeracy score		
		(1)	(2)	(3)	(4)	(5)	(6)
Ref: Man	Woman	-8.903 ***	-9.782 **	-8.684 ***	-14.837 ***	-17.101 ***	-14.524 ***
		(1.919)	(3.926)	(1.947)	(1.804)	(3.738)	(1.877)
Ref: Nacional	Foreigner	-15.965 ***	-5.008	-16.543 ***	-17.114 ***	-3.146	-17.559 ***
		(3.084)	(6.147)	(3.132)	(3.144)	(6.812)	(3.120)
Ref: 16-24 years	25-34 years	2.876	-0.080	1.889	2.471	4.115	1.015
		(3.506)	(12.849)	(3.616)	(3.668)	(15.953)	(3.746)
	35-44 years	0.991	0.658	-0.800	2.935	0.494	0.419
		(3.209)	(12.357)	(3.414)	(3.292)	(15.052)	(3.418)
	45-54 years	-8.151 **	-1.505	-9.035 **	-9.149 **	-4.671	-11.120 ***
		(3.397)	(12.870)	(3.657)	(3.865)	(15.046)	(3.974)
	55 years and more	-29.520 ***	-22.409 *	-31.184 ***	-29.006 ***	-21.841	-32.278 ***
		(3.685)	(12.257)	(3.799)	(3.957)	(15.035)	(3.845)
Ref: Self-employed	1-10 workers	-2.754	3.711	4.882	-4.734	8.821 **	9.332 **
		(3.051)	(4.151)	(4.000)	(3.050)	(4.158)	(4.095)
	11-50 workers	-2.409	0.663	7.338	-4.673	-4.999	12.463 **
		(3.180)	(10.180)	(4.524)	(3.219)	(9.867)	(4.775)
	Over 50 workers	2.243	29.489 **	12.018 **	1.994	28.040 ***	19.366 ***
		(3.694)	(12.222)	(5.079)	(3.463)	(9.028)	(5.122)
Ref: Private sector	Public sector	6.249 **			5.480 *		
		(2.922)			(2.827)		
Ref: Manager	Business owner		-7.776			-15.553 *	
			(8.565)			(8.181)	
Ref: Business owner	Salaried employee			-8.920 ***			-17.074 ***
				(3.209)			(3.252)
Ref: Agriculture, livestock farming y fishing	Mining industries	32.711 **	50.649	32.367 **	35.289 ***	22.731 **	36.145 ***
		(13.678)	(45.543)	(13.539)	(11.888)	(10.745)	(11.695)
	Manufacturing	15.362 ***	16.940 **	14.869 ***	22.822 ***	20.013 **	23.907 ***
		(4.477)	(7.265)	(4.407)	(5.185)	(7.679)	(4.856)
	Energy supply	15.555	21.023 **	16.029	27.159 **	22.229	28.919 **
		(10.775)	(8.067)	(10.625)	(11.314)	(33.302)	(11.095)
	Water supply	10.070	22.510 *	7.888	7.690	41.104 ***	7.218
		(6.835)	(12.953)	(8.467)	(9.639)	(9.197)	(10.137)
	Construction	10.492 **	4.209	9.918 **	15.981 ***	3.565	16.327 ***
		(4.529)	(7.743)	(4.506)	(5.771)	(7.544)	(5.552)
	Trade and repair	19.962 ***	8.971	19.728 ***	22.726 ***	8.510	23.473 ***
		(3.856)	(6.780)	(3.828)	(4.755)	(6.461)	(4.625)
	Transport and storage.	19.464 ***	14.811	19.861 ***	22.586 ***	17.826	24.347 ***
		(4.874)	(9.185)	(4.933)	(5.838)	(10.713)	(5.863)
	Accomodation and food s. act.	7.811	14.391 *	6.494	11.065 *	7.288	10.422 *
		(4.804)	(8.610)	(4.790)	(5.864)	(8.915)	(5.638)
	ICT	52.322 ***	45.071 ***	52.147 ***	54.597 ***	43.492 ***	55.497 ***
		(4.363)	(12.227)	(4.273)	(6.116)	(12.839)	(5.812)
	Insurance and financial act.	44.475 ***	40.544 ***	45.181 ***	52.958 ***	31.022 ***	55.588 ***
		(5.403)	(10.034)	(5.394)	(6.738)	(10.548)	(6.619)
	Real estate	16.883	46.942 ***	15.215	29.907 ***	49.769 ***	28.055 ***
		(16.319)	(9.021)	(15.789)	(11.018)	(15.980)	(9.871)
	Prof., scientíf. and tech. act.	37.757 ***	37.409 ***	37.911 ***	44.922 ***	38.363 ***	45.685 ***
		(4.408)	(7.421)	(4.292)	(5.624)	(7.449)	(5.429)
	Administr act. and support	13.338 **	28.624 ***	15.449 ***	15.982 **	22.261 **	19.853 ***
		(5.321)	(8.606)	(5.260)	(6.288)	(10.276)	(6.000)
	Public Admin.	25.855 ***	32.336 ***	31.704 ***	29.276 ***	39.043 ***	36.348 ***
		(5.682)	(12.070)	(4.686)	(5.980)	(11.392)	(5.078)
	Education	47.285 ***	48.726 ***	51.515 ***	46.222 ***	30.491 ***	51.490 ***
		(5.336)	(11.165)	(4.829)	(5.798)	(8.400)	(5.295)
	Health and social services	26.153 ***	36.750 **	28.702 ***	30.511 ***	25.522 **	33.895 ***
		(5.365)	(15.371)	(5.063)	(6.129)	(11.894)	(5.655)
	Arts and entertainment	29.918 ***	43.542 ***	29.851 ***	31.661 ***	38.941 ***	31.677 ***
		(7.890)	(12.689)	(7.908)	(9.921)	(12.255)	(9.812)
	Other services	11.469 **	4.808	15.687 ***	16.801 **	6.367	21.023 ***
		(5.352)	(9.460)	(5.199)	(6.823)	(11.752)	(6.704)
	Household services	-3.266	-4.016	-2.572	-2.035	-10.558	0.799
		(5.717)	(9.834)	(5.437)	(6.198)	(7.842)	(5.865)
	Constant	249.325 ***	254.715 ***	250.262 ***	245.950 ***	265.524 ***	246.911 ***
		(4.875)	(16.298)	(4.892)	(5.425)	(18.426)	(5.452)
	N	3246	620	3219	3246	620	3219
	R^2	0.196	0.251	0.198	0.202	0.266	0.211
	F	31.105	9.568	27.673	17.855	19.251	16.968

***, **, *: significant at 1%, 5% y 10% respectively. Standard errors in parentheses, calculated using the Jackknife2 replicaction procedure for 80 replicated weights.
Source: PIAAC and authors' calculations.

Respondents who work in large firms, of more than 50 workers, show higher scores than those from other firm size levels. These differences are significant when including the dummy that distinguishes between business owners and salaried employees, noting that those employed in firms of more than 50 workers get an average of 12 points more in literacy than the self-employed, and 19.4 points more in numeracy.

For the subsample of entrepreneurs (columns 2 and 5) the difference in favor of large companies increases up to 29.5 points in literacy and 28 points in numeracy, indicating that, *ceteris paribus*, employers with salaried employees and managers of large firms show a substantial difference in their score when compared to the business owners without employees. These results seem to confirm the hypothesis that large firms offer a more favorable environment for the individuals' human capital.

All else being constant, some sectors of activity grant a skills bonus to their workers. The score differences among sectors are found with respect to agriculture and in some branches of activity they are significant. Among those that are statistically significant, the most important correspond to the sectors of ICT; education, financial and insurance activities, professional, scientific and technical activities, mining and quarrying, public administration, health, and arts, recreation and entertainment activities. In contrast, the employed workers in household services have a skill penalty.

As for the effect of the introduction of the productive variables which allow us to compare the occupational groups, the consequences are less than those observed by introducing educational variables. Being a public employee retains a positive effect, although less significant, which is to be expected, since we have already differentiated the sectors of activity and the public employees are largely engaged in education and health services and in the public administration. Finally, once the variables of location in the productive fabric are taken into account (firm and sector), being a salaried employee as opposed to a business owner means a lower skill level.

Joint effect of the demographic, educational and productive characteristics on the PIAAC scores

Finally, Table 6.8 presents the results of considering the three groups of determinants all together, as well as the occupational dummies. The joint explanatory power slightly improves compared to the case where educational variables were already introduced. These variables retain all of their significance (sign and importance), so do the demographic variables.

As for the variables representing the productive fabric, the size of the firms practically loses its significance, probably because its effects on the scores are now channeled through the higher educational level of those employed in the large firms. However, some sectors retain their positive impact on performance, although in general the value of this effect is now less. The sectors of information and communications, education, financial and insurance activities and arts, entertainment and recreation activities are those that show the highest associated score, thus indicating that they are environments favorable to human capital.

Table 6.8. OLS regressions of the PIAAC scores in literacy and numeracy, by demographic, educational and productive characteristics

		Dependent variable: PIAAC Literacy score			Dependent variable: PIAAC Numeracy score		
		(1)	(2)	(3)	(4)	(5)	(6)
Ref: Man	Woman	-11.110 ***	-11.999 ***	-10.848 ***	-17.204 ***	-19.418 ***	-16.823 ***
		(1.746)	(3.695)	(1.777)	(1.633)	(3.602)	(1.706)
Ref: National	Foreigner	-16.975 ***	-4.888	-17.049 ***	-18.365 ***	-3.005	-18.265 ***
		(2.801)	(5.970)	(2.878)	(2.737)	(6.641)	(2.785)
Ref: 16-24 years	25-34 years	-2.058	-12.292	-3.200	-2.417	-8.535	-4.031
		(3.114)	(11.720)	(3.198)	(3.162)	(15.088)	(3.274)
	35-44 years	-3.156	-12.257	-4.764	-0.944	-12.750	-3.297
		(2.880)	(11.572)	(3.083)	(3.021)	(14.551)	(3.171)
	45-54 years	-8.769 ***	-11.000	-9.958 ***	-9.355 ***	-14.674	-11.694 ***
		(3.005)	(11.896)	(3.298)	(3.493)	(14.512)	(3.672)
	55 years and	-24.814 ***	-27.061 **	-26.520 ***	-23.277 ***	-26.641 *	-26.747 ***
		(3.479)	(11.383)	(3.706)	(3.681)	(14.351)	(3.714)
Ref: Up to primary	Lower secondary	15.111 ***	16.461 ***	15.537 ***	17.925 ***	16.700 ***	17.886 ***
		(2.748)	(5.401)	(2.833)	(2.791)	(5.094)	(2.864)
	Upper secondary	31.980 ***	26.907 ***	32.100 ***	38.049 ***	31.873 ***	37.692 ***
		(2.877)	(5.194)	(3.013)	(3.169)	(5.651)	(3.274)
	Tertiary-type B	36.131 ***	38.955 ***	36.480 ***	42.666 ***	46.448 ***	42.332 ***
		(3.082)	(7.393)	(3.190)	(3.206)	(7.495)	(3.211)
	Tertiary-type A	58.642 ***	58.059 ***	58.850 ***	61.579 ***	59.019 ***	61.088 ***
		(3.134)	(6.457)	(3.261)	(2.979)	(5.991)	(3.113)
Ref: Self-employed	1-10 workers	-0.099	2.967	3.322	-2.062	7.946 *	7.686 *
		(2.695)	(4.076)	(3.906)	(2.746)	(4.177)	(4.072)
	11-50 workers	-1.014	-5.637	3.120	-3.235	-11.738	8.209 *
		(2.812)	(11.171)	(4.398)	(2.875)	(10.826)	(4.584)
	Over 50 workers	0.334	16.348	4.264	0.034	14.773	11.502 **
		(3.255)	(13.582)	(4.913)	(3.121)	(10.884)	(4.969)
Ref: Private	Public sector	0.299			-0.595		
		(2.442)			(2.397)		
Ref: Manager	Business owner		0.297			-8.147	
			(9.476)			(9.422)	
Ref: Business owner	Salaried employee			-4.108			-12.226 ***
				(3.239)			(3.169)
Ref: Agriculture, Livestock farming y	Mining and quarrying	20.830 *	30.063	20.916 *	21.227 **	-0.111	22.726 **
		(11.069	(51.959)	(11.068)	(9.835)	(20.548)	(9.778)
	Manufacturing	4.236	7.554	3.894	10.461 **	9.597	11.830 ***
		(4.018)	(7.143)	(3.995)	(4.610)	(7.706)	(4.428)
	Energy supply	-3.162	-13.776	-3.063	6.435	-12.091	8.055
		(10.197	(14.578)	(10.189)	(11.815	(49.519)	(11.841
	Water supply	5.693	-0.819	3.511	2.873	18.599	2.522
		(6.760)	(9.185)	(8.079)	(8.931)	(17.811)	(9.361)
	Construction	4.584	0.018	4.069	9.560 **	-0.767	10.015 **
		(3.719)	(6.947)	(3.770)	(4.674)	(6.505)	(4.542)
	Trade and repair	11.023 ***	7.357	11.216 ***	12.691 ***	6.557	13.952 ***
		(3.586)	(6.713)	(3.588)	(4.401)	(6.325)	(4.301)
	Transport and storage	11.118 **	9.022	10.824 **	12.922 **	10.951	14.068 ***
		(4.442)	(9.793)	(4.443)	(5.301)	(10.680)	(5.322)
	Accommodation and food s. act.	1.055	12.531	0.036	3.583	4.839	3.317
		(4.144)	(8.568)	(4.183)	(5.236)	(9.174)	(5.060)
	TCT.	25.424 ***	12.469	25.422 ***	26.314 ***	11.220	27.664 ***
		(4.560)	(11.699)	(4.525)	(5.753)	(12.260)	(5.677)
	Insurance and financial act.	14.741 ***	17.689 *	15.176 ***	21.433 ***	7.330	24.095 ***
		(5.250)	(9.146)	(5.297)	(6.251)	(10.504)	(6.214)
	Real estate	-0.859	19.597	-1.538	10.266	21.722 **	9.588
		(15.803	(11.883)	(15.703)	(10.658	(9.709)	(10.139
	Prof., scien. and tech. act.	8.206 *	7.920	8.036 *	14.239 ***	8.618	14.957 ***
		(4.555)	(8.322)	(4.554)	(5.353)	(8.406)	(5.280)
	Administr act. and support services	3.710	11.963	5.329	5.037	4.133	8.582
		(4.425)	(8.907)	(4.399)	(5.605)	(12.149)	(5.367)
	Public Admin.	9.498 *	14.745	9.841 **	11.636 **	20.758 *	13.353 ***
		(5.093)	(12.282)	(4.215)	(5.583)	(10.798)	(4.702)
	Education	17.145 ***	24.620 **	17.839 ***	15.286 ***	5.760	17.275 ***
		(4.972)	(11.663)	(4.611)	(5.083)	(8.878)	(4.598)
	Health and social services	5.789	7.995	5.924	8.905	-3.379	10.095 *
		(4.971)	(14.957)	(4.758)	(5.447)	(11.738)	(5.130)
	Arts and entertainment	17.204 **	18.229	16.144 **	17.361 *	12.583	16.555 *
		(7.258)	(13.998)	(7.367)	(9.466)	(13.713)	(9.530)
	Other services	2.079	-1.636	3.884	6.265	-1.427	8.200
		(5.116)	(9.489)	(4.924)	(6.318)	(11.557)	(6.243)
	Household serv and prod.	-8.059	-6.158	-8.358	-7.268	-13.103	-5.437
		(5.220)	(8.706)	(5.068)	(5.621)	(8.149)	(5.358)
	Constant	235.043 ***	239.265 ***	236.087 ***	228.905 ***	249.640 ***	230.355 ***
		(5.132)	(16.119)	(5.224)	(5.379)	(18.943)	(5.480)
	N	3245	620	3218	3245	620	3218
	R^2	0.336	0.367	0.336	0.344	0.383	0.349
	F	42.506	11.488	45.011	34.037	21.666	34.726

***, **, *: significant at 1%, 5% y 10% respectively. Standard errors in parentheses, calculated using the Jackknife2 replicaction procedure for 80 replicated weights. Source: PIAAC and authors' calculations..

As regards the significance of the occupational dummies when looking at all the variables together, only the negative effect on the PIAAC-M of being a salaried employee instead of a business owner is maintained, all else being constant (column 6). Instead, once the demographic, educational and productive environment characteristics of the employed are taken into account, the difference between the groups of business owners and managers or between public and private employees is no longer significant (columns 2 and 5).

CONCLUSIONS

The PIAAC scores in literacy and numeracy and the analyses presented in this study confirm that the human capital of employed workers in Spain is generally at an intermediate level. It has been proved that education is a key determinant but within each educational level there are individuals with very different PIAAC scores, something which reduces the accuracy of the usual human capital indicators based on the levels of education completed.

We have found that some demographic characteristics such as gender, nationality and age have robust effects on the skill levels reached. The scores are lower among women, foreigners and those over 45 years old. The interpretation of the tendency of the first two factors requires a deeper analysis of the effects of other psychosocial variables provided by PIAAC, but which have not been considered in this study. As for the effect of age, as well as looking for explanations in that direction, we put forward the hypothesis of the presence of decreasing skills returns starting from the ages that, in Spain, are often considered for early retirement.

The study confirms the existence of productive environments (sectors of activity and firms) that are more favorable to human capital and, as a result, we find higher skill levels among those employed in them. In this sense, the sectors that stand out are those more related to knowledge, such as ICT, education, financial and insurance activities, as well as arts, entertainment and recreation activities. As for the role of the firm sizes, the higher skill levels of workers in larger firms are derived from their higher levels of education, as there are no additional significant differences associated with size such as those which are seen in the case of the sectors. So, it can be said that the advantages that the larger firms have in terms of human capital are associated fundamentally with the fact that their selection criteria of human resources provide as a result a larger proportion of workers with higher levels of education.

In relation to the question posed in the introduction about the influence of the importance given to educational credentials in the selection procedures of public and private employees on their levels of human capital, the answer is affirmative: the differences observed in the PIAAC scores in favor of public employees are explained by differences in their educational levels. Once this circumstance is taken into account there are no other significant differences associated with the public or private sectors, nor were any observed in the case of large firms. This result indicates, however, that by taking the levels of education completed into account in the recruitment process, with all the relevant nuances, we have a good predictor of literacy and numeracy skills reached by the employed workers, with everything else being constant.

Finally, in the study we have explored whether entrepreneurs, which in Spain are known to have medium to low levels of education and are self-employed, have personal features that give them advantages of human capital because of their entrepreneurial nature. Specifically, we have analyzed whether these differences are reflected in their literacy or numeracy scores and the answer is clearly negative. We can, therefore, assert that the role of educational credentials is relevant in the case of entrepreneurs, and when these are low their average skill levels will probably also be low.

This result is particularly relevant for the self-employed persons which have greater educational disadvantages. It is important to note that this kind of entrepreneurs possess, on average, low literacy and numeracy skills and often have to deal with decisions and assess risks and problems associated with their own independent professional activity. In this regard it should be noted that when selecting managers, who also carry out entrepreneurial tasks but are not self-selected, the markets and other human resources specialists do consider acquired education to be important. The PIAAC data clearly confirm that, in this case, their skill levels are substantially higher than those of the business owners, with or without salaried employees.

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7. Differences between cohorts in Spain: The Role of the General Law of the Education System and an analysis of the depreciation of human capital

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7. DIFFERENCES BETWEEN COHORTS IN SPAIN: THE ROLE OF THE GENERAL LAW OF THE EDUCATION SYSTEM AND AN ANALYSIS OF THE DEPRECIATION OF HUMAN CAPITAL

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ABSTRACT

PIAAC (Programme for the International Assessment of Adult Competencies) data show intergenerational differences in cognitive skills of the Spanish adult population with regard to Numeracy and Literacy. Two issues are discussed in this paper: 1) The effect of educational reform carried out in 1990 with the adoption of the LOGSE (Spanish acronym for General Law of the Education System), and 2) factors affecting development of cognitive skills through age. First, we estimate that the implementation of the LOGSE had a negative effect on math and literacy skills to the cohorts affected by it. Although significativity of this finding varies depending on the specific functional specification of "cohort/age" effect, in no case it is obtained a positive effect of the reform. On the other hand, we find that being employed, the use of Numeracy and Literacy affect cognitive abilities and their evolution with age. Specifically, people with these characteristics seem to be able to improve their skills to older ages, thus delaying the age of human capital depreciation.

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Keywords

Human Capital, Spanish Cohorts, Cognitive Skills, LOGSE; PIAAC; educational reform.

INTRODUCTION

This paper is aimed at investigating two aspects related to the differences in Numeracy and Literacy skills among the different cohorts of the Spanish population of working age. Firstly, we try to estimate the effect of the General Law of the Education System (LOGSE in Spanish) which affected, in varying degrees, to those born after 1976. Secondly, we carry out a descriptive analysis of the "cognitive skills curve" for different age groups and their relationship to different factors such as: employment situation; the use of numeracy and literacy; and formal education.

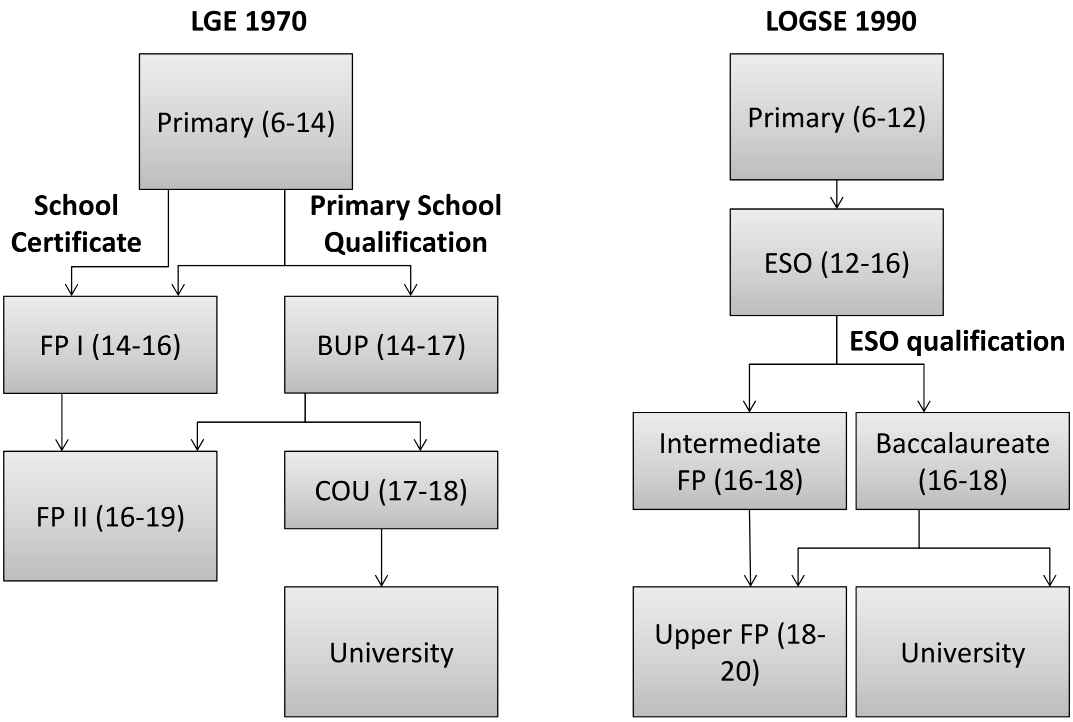
The LOGSE was passed in 1990 and was a modification of the Spanish educational system, above all for compulsory and post-compulsory secondary education with respect to the previous system of the General Education Law (LGE in Spanish) of 1970. Figure 7.1 shows the main differences in the structure of the two laws. With the LGE compulsory primary education ended at the age of 14. After that, those pupils who finished primary school successfully obtained the Primary School Qualification and could continue their studies through 1st level Vocational Training (FP in Spanish) or by continuing with the Baccalaureate or secondary school (BUP in Spanish). The rest obtained a School Certificate and only had access to FP. Under LOGSE this scheme changed so that primary education ended at age 12, then Compulsory Secondary Education (ESO in Spanish) started, up to 16 years old. From here only those students who obtained ESO qualification could continue with their studies, either in Baccalaureate or vocational training (FP). For those students who failed, non compulsory Social Guarantee Programmes (PGS) were established aimed at providing basic education for their incorporation into working life and as an alternative route of access to secondary vocational training.

Therefore, we can see at least two ways in which the structure of the educational system under the LOGSE may have affected student performance. Firstly, students are required to study two additional years of secondary education and as a result are not segregated according to their orientation (vocational or academic) until the age of 16. And secondly, there is no room in the education system via the FP for those students who fail compulsory education because this requires the ESO qualification. While they have an alternative route of access to FP through PGS, it is at the expense of a delay in time. The effects of these two factors may be various from a theoretical point of view. On the one hand extension of schooling age may positively affect those who would otherwise leave school at an early age. On the other hand, the effect of having the students grouped in the same classrooms implies that peer effects arise as a consequence of the fact that the old “bad students” are now in the same classrooms along with “good peers”. Therefore, the bad (good) peers are affected positively (negatively) as the average quality of their classmates will be higher (lower). To the extent that the greater benefits for less advantaged students outweigh the disadvantages for the best students, the overall effect will be positive. Hoxby (2000) finds evidence of this kind of asymmetry. Finally, the fact that the ESO qualification is required in order to continue studies (either vocational or academic) implies that those students who fail remain excluded to some extent from the main following levels of education. Note that with the previous LGE there was at least room for these failed students in vocational education (FP) from age 14 (see a reflection of this in Cabrera, 2007).

Due to the lack of appropriate statistical information to date, analysis of the effects of the LOGSE has been scarce. However, we can highlight the work of Felgueroso et al (2013) who use data from the Labour Force Survey (EPA in Spanish) for cohorts potentially affected by the LOGSE. Owing to the fact that in EPA there is no possibility of directly identifying those individuals who studied under the LOGSE, they use an identification strategy based on assigning an index of exposure to LOGSE to each individual, measured as a proxy of the probability that a person within an given age range and region has studied under the LOGSE. The econometric analysis leads them to the estimation of a negative effect for males, increasing dropout rates, and positive for females, decreasing school failure. Also, Lacasa (2006) makes a descriptive analysis which shows that the implementation of the LOGSE coincides with a shift and decay of some indicators of the educational system, for example: the enrollment rate at age 17; school life expectancy at age six; percentage of population with only lower secondary education at age 18-24; rate of upper secondary graduates; rate of people aged 18 taking university access exam, and; rate of students enrolled at the university at age 20. On the other hand, De Miguel-Diaz et al (2002) analyze the educational performance of students from different Spanish universities (Barcelona, Oviedo, Basque Country, Salamanca and Zaragoza) depending on the type of baccalaureate they have studied, LOGSE or LGE. Their results indicate that there are no systematic and determining differences between these two groups in aspects of the academic record such as: average baccalaureate grade; university access exam; proportion of courses passed during the degree; or completion of the degree in the years indicated in the syllabus.

In this study we used data from the Programme for the International Assessment of Adult Competencies (PIAAC) to try to estimate the effect of the LOGSE reform on numeracy and literacy skills of the Spanish adult population. This is possible because in PIAAC they assess individuals from different cohorts who studied under different education laws, LOGSE and previous laws. Applying the same methodology as in Felgueroso et al (2013) we can estimate whether a relationship exists between the degree of exposure to LOGSE and competencies. The analysis has at least two new and interesting aspects. Firstly, the dependent variable under study is the scores of an internationally standardized test that attempt to measure the degree of ability of individuals in order to function in their personal and professional life. Therefore, the performance of different individuals are assessed, those who studied LOGSE and those who did not, by the same criteria. In the case of De Miguel-Diaz et al (2002) they used some measurements that may not be homogeneous, e.g. baccalaureate performance assessments or university access exams are different for students under LOGSE and LGE. Also, the dependent variable used here measures ability or skill, unlike Felgueroso and others (2013) who use the school dropout rate. Although both variables are highly correlated they do not necessarily affect peoples' lives in the same way. Secondly, the availability of data for different cohorts allows us to estimate the relationship between the degree of implementation of LOGSE once we control for different trends related to the effect of the year of birth. For example, we might find a negative relationship between the implementation of the LOGSE and numeracy competence because those who studied under the LOGSE are younger and have less experience. For this reason we estimate different functional specifications that try to capture the age or cohort effect and to differentiate it from the impact of the LOGSE. The results we obtain indicate that the LOGSE was not succeeded when it comes to increasing numeracy and literacy skills of the Spanish population. In fact the effect is always negative, but the significance of it varies according to the functional specification of the age/cohort trend.

Figure 7.1. Basic structure of the Spanish educational system under the LGE and the LOGSE.



Source: Cabrera (2007) and own elaboration

In this paper we also intend to analyze the factors affecting the relationship between cognitive skills and age. The evidence suggests that there is a more or less generalized pattern with respect to the relationship between cognitive skills and age. In particular, there appears to be a first section in which scores increase until the age of 25-35 while later decrease continuously for older ages. See for example Desjardins and Jonas (2012) who analyze the effect of age on literacy for a set of countries that participated in IALS (*International Adult Literacy Survey*) and ALL (*Adult Literacy and Lifeskills Survey*) studies. Although the specific profile may vary by country, all of them have in common a negative relationship between cognitive skills and age, therefore having a depreciation effect on human capital.

In the case of Spain we find this same relationship for the numeracy and literacy skills assessed by PIAAC. The intention here is to identify what factors can modify that relationship between skills and age. In other words, we want to study how some variables can affect the depreciation of human capital, or what we will call the *age-skill curve*. For example, Villar (2013) carries out an intergenerational comparison of numeracy and shows that this relationship is general for all educational levels. However there are nuances like the fact that the relative advantage of those with college degree increases with age (see Graph 8.3 on Villar, 2013). There are several theories which suggest that the depreciation of skills happens when these are no longer used, or alternatively that they are maintained if they are put into practice (Reder, 1994, Statistics Canada and OECD, 1995, Staff et al, 2004; Pazy, 2004; Grip et al, 2008). With this in mind we analyzed, from a descriptive point of view, the effect of being employed, and the use of skills at home and at work.

Just as pointed out by Desjardins and Jonas (2012), estimating the age effect on cognitive skills requires differentiating it from other effects such as the cohort effect. Since PIAAC is a cross-sectional study we cannot distinguish between the two variables, though our intention is not to estimate the effect of age on skills but to describe how the relationship between the two variables varies once we control for other factors. Where a factor affects the relationship between age and skills, this may happen in two different ways:

a) A factor equally affects the skills of different age groups. [2] For example, when the work activity improves numeracy skills for everyone by the same amount. In this case, we shall say that this factor affects the starting point of the *age-skill curve* but not the slope or rate of depreciation.
b) Alternatively a factor may affect various age groups differently. In this case we shall say that this factor affects the rate of depreciation or the slope of the curve.

The analysis leads us to conclude that working (being employed) and the use of numeracy and literacy skills affect differently the various age groups. That is, these factors affect both the starting point and the slope of the age-*skill curve*.

The presentation of this study has two clearly distinct parts corresponding to the two analyses we intend to carry out. Firstly, the LOGSE analysis: we explain the methodological details; we approach the data through a descriptive analysis, and finally we present the results of the econometric analysis and the conclusions. Secondly, we study the relationship between skills and age: we present the methodology and show the results to reach a conclusion. Finally we include a section of general conclusions.

[2] Since PIAAC is a cross-sectional survey there are hardly any differences between the age (year of birth) and the cohort variable since all individuals were assessed in the same year of the survey. However, for this second analysis of the depreciation of human capital it seems more convenient to use the age variable.

THE LOGSE REFORM

Given that in PIAAC database there is no information on the educational law under which each individual studied, we have to resort to the available external information about the LOGSE reform process. The law was passed in 1990, when it was progressively put into operation until its full implementation in the 2002/03 academic year. In this transition period both systems coexisted in such a way that, even in the same age group, there were some students who studied under the LOGSE and others under the LGE. The degree of implementation of the LOGSE varies for each of these transition years and also for the different Spanish Autonomous Regions. The strategy used in this study is to calculate a proxy variable for the probability that an individual has studied the LOGSE depending on their year of birth and region. If the LOGSE has any effect there should be a relationship between this variable and the results in numeracy and literacy skills. This strategy is a similar methodological approach to that already used by Felgueroso et al. (2013).

Methodology

Calculation of the variable of implementation of the LOGSE

To calculate our main explanatory variable we use the statistical directories of the Ministry of Education, Culture and Sports, called "The education figures in Spain" (*Las cifras de la educación en España*). In these directories we have access to the percentage of students who studied LOGSE over the total number enrolled for each academic year and autonomous region.[3] Being able to differentiate between those that studied different educational stages: ESO first stage, comprising 1st and 2nd year of ESO; ESO second stage, 3rd and 4th year of ESO; and Baccalaureate (1st and 2nd year). An important aspect in the process of implementing the LOGSE is that there were students who studied part of their academic life under LGE and part under LOGSE. For example, an individual may have studied primary school under the LGE up to 14 years old, obtained the Primary School Qualification (see Figure 7.1), and also continued their studies under the LOGSE system, joining the corresponding level according to her age (in this case 3rd year of ESO). There may even have been students who joined the LOGSE in Baccalaureate at age 16, having studied until then under the old system.

Taking the above into account, we differentiate up to three different measurements:

a) *ESO1*. The "probability" that a student has studied the first stage of ESO;
b) *ESO2*. The "probability" that a student has studied the second stage of ESO, and;

[3] This statistical information can be accessed in the website of the Ministry of Education, Culture and Sport in the following link:

http://www.mecd.gob.es/servicios-al-ciudadano-mecd/eu/estadisticas/educacion/indicadores-publicaciones-sintesis/cifras-educacion-espana/2000.html

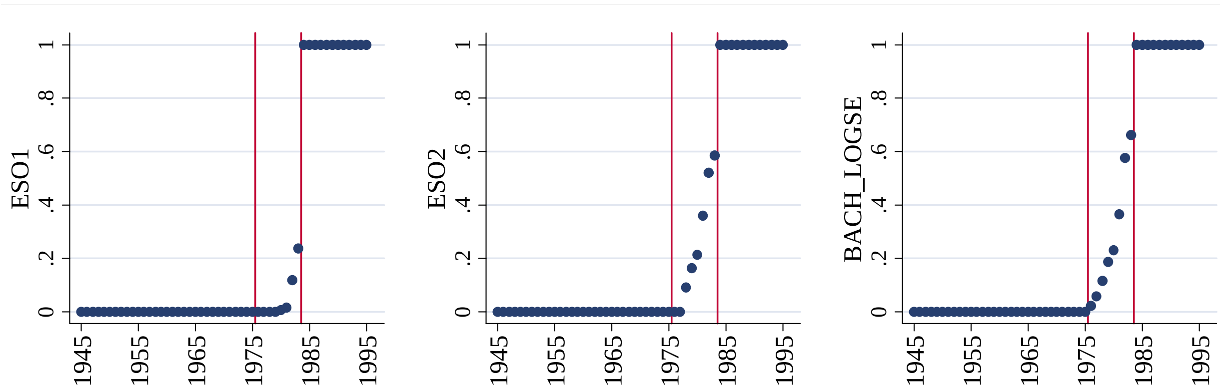
c) *BACH_LOGSE*. The "probability" that a student has studied the LOGSE Baccalaureate.

We calculate the *ESO1* variable as the proportion of students studying the first stage of ESO in the academic year that would correspond to study 2nd year of ESO according to date of birth. So, for example, those born in 1983 must have started studying 2nd year of ESO (or analogous level under the LGE) at age 13 in the 1996-1997 academic year, so that they are assigned the proportion of students in 2nd year of ESO in that academic year. As for *ESO2,* it is the proportion of students studying the second stage of ESO in the academic year that would correspond to 4th year of ESO. Finally *BACH_LOGSE* is the proportion of students studying the LOGSE Baccalaureate for the academic year in which they should have studied 2nd year of the same stage. The value of these variables is different for individuals with different dates of birth and from different regions. Resulting from the creation of the above variables we can distinguish three groups of cohorts:

I. PRE-LOGSE. Those born between 1945 and 1975. They all studied under the LGE or previous systems.
II. TRANSITION. Those born between 1976 and 1983 that have a certain probability of having studied LOGSE at least some stages of LOGSE.
III. POST-LOGSE. Those born between 1984 and 1995. Those who have studied only under the LOGSE system.

Graph 7.1 shows the average value of the three variables of implementation for the different cohorts. The red vertical lines in this graph delimit the three periods considered. It can be seen that the degree of implementation of the LOGSE grows throughout the whole period of TRANSITION. However, there is more variability in the case of the ESO2 and BACH_LOGSE variables than in the case of ESO1.

Graph 7.1. Variables of implementation of the LOGSE by year of birth



The Econometric model and control for the year of birth trend.

To calculate the effect of the variables of implementation of the LOGSE we estimate an econometric model of Ordinary Least Squares (OLS) in which we controlled for different specifications of the birth year trend. The objective of this exercise is to control for the extent to which differences between the LOGSE and previous generation are due to a trend of the cohort effect. Cohort effects relate to differences in age or experience and particularly any other factor affecting skills differences between the different cohorts. Therefore, we estimate the econometric model with up to 10 different specifications of the effect of the year of birth depending on the number of different trends that are estimated (one, two or three) and the type of trend (linear, quadratic and polynomial of 3rd and 4th degree). In Table 7.1, we can see the different models from (1) to (10) that are going to be estimated. For models (1) and (2) respectively linear and quadratic trends are estimated and three different trends coincide with the three previously mentioned cohort groups: PRE-LOGSE, TRANSITION and POST-LOGSE. For models (3) and (4) we distinguish between two different trends - the first trend coincides with the period PRE-LOGSE and the second trend is the other two together (TRANSITION AND POST-LOGSE). In the case of models (5) and (6) there are also two distinct trends but in this case the first two periods PRE-LOGSE and TRANSITION are grouped together. Finally, models (7) to (10) consider a single trend with up to four types of specification: linear, quadratic, and polynomial of 3rd and 4th degree, respectively.

Besides the effect of year of birth we controlled for a series of covariables: gender; parental education; individuals' health; employment situation; type of occupation; level of education; area of expertise; and if the individual is continuing with his/her formal education. We also include a binary variable for each region in order to control for differences between autonomous regions.

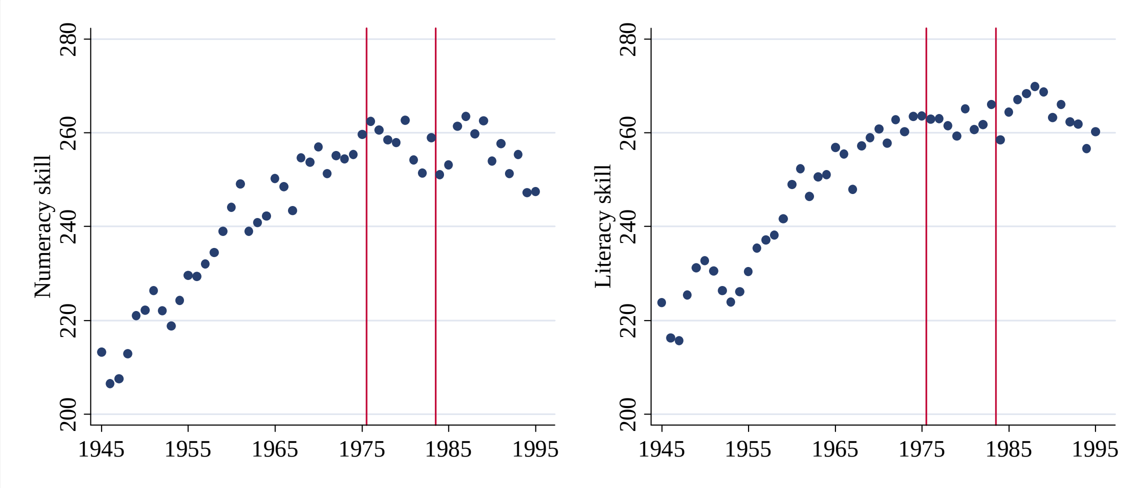
Table 7.1. Specifications of the effect of birth year

	Number of trends considered			
Type of trend	**3 Periods:** - 1945 to 1975 - 1976 to 1983 - 1984 to 1995	**2 Periods:** - 1945 to 1975 - 1976 to 1995	**2 Periods:** - 1945 to 1983 - 1984 to 1995	**1 Period:** - 1945 to 1995
Linear	(1)	(3)	(5)	(7)
Quadratic	(2)	(4)	(6)	(8)
Polynomial G.3				(9)
Polynomial G.4				(10)

Descriptive Analysis

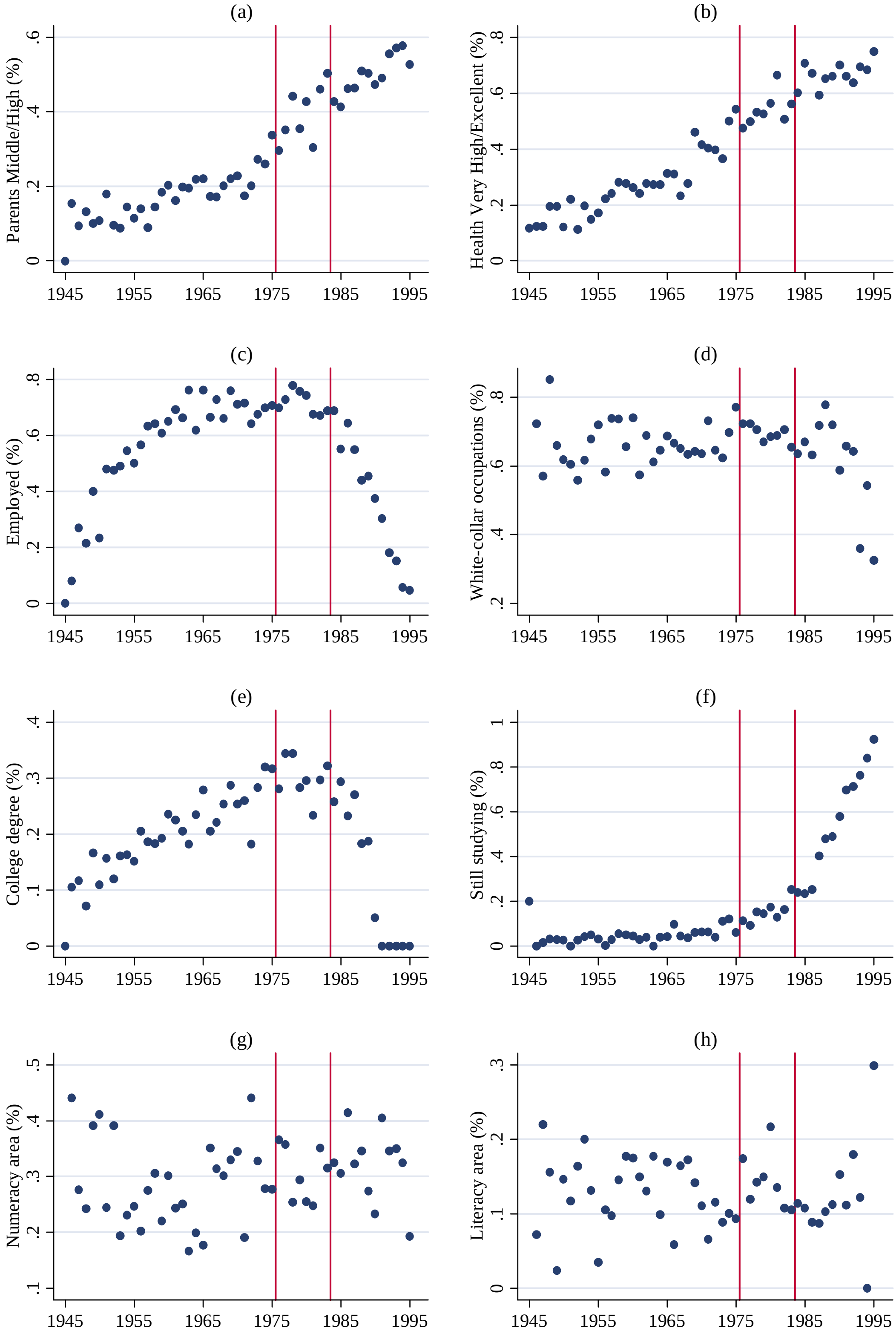
Graph 7.2 shows the average score in numeracy and literacy competence by different cohorts. It can be seen that the beginning of the reform coincides with a change in the slope of the scatter plot. Specifically, the score in numeracy decreases during the process of TRANSITION and once it ends a short period begins (between 1984 and 1989) in which the numeracy score improves again. Beyond attributing this effect directly to the LOGSE there appears to be evidence of the existence of an anomaly that is worth studying. In the case of the literacy competence this anomaly is also observed, although apparently to a lesser extent. For example, during the period of TRANSITION the scatter plot seems to have a flat evolution, and goes back to having a positive slope at the beginning of the POST-LOGSE period.

Graph 7.2. Scores in numeracy and literacy by year of birth



With the aim of finding some explanation for the change in the trend observed in PIAAC scores, Graph 7.3 shows the evolution of different covariables that could be behind this effect. For example, the percentage of individuals who have at least one parent with middle (secondary) or high (college) education is in panel (a) of Graph 7.3. This variable shows no change in trend for the TRANSITION group therefore it is a poor candidate for explaining the decay of skills for that period (see Lacasa, 2006). The same can be said for those individuals who reported very good or excellent health (represented in panel b) which has a continuous positive slope for the three generational groups considered. In panel (f) of the same graph we see that the proportion of individuals who are studying at the moment is always higher for younger cohorts. Thus, it appears that the shift in the skills in Graph 7.2 have no relationship with these variables described. On the contrary, there is a shift in the percentage of employed individuals (panel c), the percentage of white-collar occupations (panel d) and the percentage of people with college degree (panel e). All these variables appear to decrease during the period of the LOGSE TRANSITION contrasting with the upward trend of PRE-LOGSE period. Finally we consider the percentage of individuals having a secondary or university degree directly related to mathematics or science (panel g) and humanities (panel h), although there seems to not be a clear pattern for the periods considered.

Graph 7.3. Characteristics of the individuals by year of birth



Graph

Results

In LOGSE analysis we only consider native individuals in order to have a more homogeneous group who has been educated in Spain most likely. In Table 7.2 we see the detailed results of the estimation of model (1) (see Table 7.1 above) for numeracy and literacy. The ESO2 variable captures the effect of LOGSE once we control for a linear trend, different for the three periods considered, and other covariables. Since this variable is a probability measured per unit, the coefficient should be interpreted as the variation of skills as a result of moving from a probability of 0 to 100% of having studied under LOGSE. In other words, it would be analogous to the differential effect for an individual who has studied under LOGSE with respect to those who did not. The estimated effect of the LOGSE is negative and significant at 1% level, and very similar for Numeracy and Literacy, around -18 points of the PIAAC score. As for the birth year variable is included in differences with respect to 1984 and it has been divided by 10 so that the interpretation of the estimated coefficients is the effect of belonging to a cohort 10 years younger. To consider the different trends this variable is interacted with other binary variables that indicate the specific period, so that they have a value of 1 for individuals born in the specific period and a value 0 otherwise. The results indicate a significant positive trend for the first two periods PRE-LOGSE and TRANSITION. For the POST-LOGSE period the trend is not significant.

With respect to other variables males obtain significantly higher scores than females for the two types of skills assessed. The result for numeracy is consistent with other studies which show that males tend to be better at maths. However, it contrasts with the results of standardized assessments for 15 year old students such as PISA (*Programme for International Student Assessment*) which show that girls have better results in reading (see Stoet and Geary, 2013, for an international comparison; and the Spanish report for PISA 2009 on literacy, National Institute for Educational Evaluation, 2010). However, in Chapter 3 of Volume I of the Spanish PIAAC report it is shown that gender differences in literacy is not significant for young cohorts.

As for parental education in the model constant we included individuals who have a father and mother with primary education or less (low) and compared them with those who have at least one parent with secondary education (middle) and those who have at least one parent with tertiary education (high). The effect of having parents with high or middle education is positive for both competences. The effect of health is complex because those individuals who have very good health get better results than those with excellent health (reference group). This implies that health has some negative effect. One possible explanation for this result is the existence of endogeneity. For example, in the second part of this study found that those who work have better skills, which can also have a negative effect on health compared to those who do not work. Nonetheless, those with fair or poor health obtain a lower score, which is interpreted as a positive relationship between health and cognitive abilities. As for employment status, individuals who are employed obtain a significantly higher score than inactive individuals in the case of numeracy. Also, those who have white collar occupations, both the skilled and semi-skilled, have significantly higher scores compared to unqualified blue-collar workers for both disciplines. Finally, variables that have more influence on the results are those related to formal education. For example, those with college degree have around 55 points more than individuals with primary education or no education. The model also includes some variables which indicate whether the individual has completed studies related to Mathematics and Sciences (numeracy area) or related to Arts and Humanities (literacy area). The constant includes the rest of studies that are not specialized in either of the two disciplines assessed. These variables are interacted with the education variables, which allow us to estimate a different effect for those with 2nd Stage Secondary education, on the one hand, and those with university education, on the other hand. Interestingly, those who studied a degree related to Mathematics obtain significantly higher scores in both numeracy and literacy. However, those with literacy related studies are no different to those with unspecialized studies. Finally, we include a variable which shows whether the individual is still studying for an official qualification, which turns out to be positively related to PIAAC score in both competences.

Table 7.3 includes different variations of the analysis presented in Table 7.2 for the model (1). Ten different specifications of the effect of birth year are included (see Table 7.1 above). Each of these models has been estimated for the three independent variables created (ESO1, ESO2 and BACH_LOGSE) both for numeracy and literacy. This makes a total of 60 estimations (10×3×2). First thing to notice is that for 59 of the estimations the effect is negative, and 37 of them are also significant. The effect is positive and not significant for only one of the estimations. Thus, there are differences in the effect size and its statistical significance. For example, if we consider the linear trends (models 1, 3, 5 and 7) we estimate a stronger and more significant effect than for the quadratic models (2, 4, 6 and 8) or polynomial (9 and 10). The type of variable considered to identify the LOGSE effect also appears to influence (to a less extent) the results: the effect is systematically lower for ESO1 than for ESO2 and BACH_LOGSE. Also for some models the significativity is lower in the case of ESO1 (see models 6, 8 and 9). Finally, the significativity of the estimated effect is more robust in the case of literacy, since this holds for quadratic models 2 and 4, which is not the case for numeracy.

Table 7.2. Estimation of the LOGSE effect on Numeracy and Literacy. Model (1): 3 linear trends

Variables	Numeracy	Literacy	Variables	Numeracy	Literacy
ESO2	-18.6***	-18.3***	**Occupation** (Cons: Unskilled blue-collar)		
	(2.9)	(3.5)	Semi-skilled blue-collar	3.6	0.8
Trends:				(2.7)	(2.8)
Birth year×PRE.	8.6***	9.3***	Semi-skilled white-collar	8.4***	6.3**
	(1.2)	(1.2)		(2.6)	(2.6)
Birth year×TRAN.	15.0***	20.1***	Skilled white-collar	12.1***	9.7***
	(4.9)	(4.4)		(2.8)	(2.8)
Birth year×POST.	5.5	2.7	Has not worked in 5 years	4.6	4.5
	(4.1)	(4.5)		(2.5)	(3.2)
			Educational level (Cons: Primary or none)		
Male	12.3***	5.9***	Sec. 1st stage	23.9***	20.2***
	(1.5)	(1.4)		(2.4)	(2.3)
Parent education (Cons: E. low)			Sec. 2nd stage	37.7***	34.1***
				(2.6)	(2.5)
E. middle	2.0	3.2**	Tertiary	55.8***	53.4***
	(1.5)	(1.5)		(2.3)	(2.7)
E. high	9.8***	8.9***			
	(2.3)	(1.9)	**Area of studies** (Cons: Unspecialized)		
Health (Cons: excellent)			Area-num × Tertiary	16.1***	10.3***
Very good	3.7*	4.9**		(2.8)	(2.7)
	(2.1)	(1.9)	Area-num ×Sec. 2nd E	12.5***	7.8***
Good	1.4	1.0		(2.5)	(2.4)
	(2.0)	(1.8)	Area-lit × Tertiary	-3.3	4.2
Fair	-4.4*	-5.1**		(3.0)	(3.7)
	(2.4)	(2.2)	Area-lit ×Sec. 2nd E.	4.7	5.6
Bad	-16.1***	-20.2***		(3.9)	(3.7)
	(4.3)	(4.0)			
			Currently studying	12.3***	14.5***
Employment status (Cons: inactive)				(2.6)	(2.2)
Employed	5.0**	0.6	Observations	4,967	4,967
	(2.0)	(2.1)	R2 (%)	46.7	45.6
Unemployed	-2.4	-3.3			
	(2.5)	(2.4)			

Note 1: *, ** and *** mean that the coefficient is significant to 10%, 5% or 1%, respectively.

Note 2: Standard errors are shown in brackets and have been calculated following the methodology of the PIAAC study, using 10 plausible values for each competence and 80 replications.

Note 3: The estimations control for a series of binary variables representing each region.

Table 7.3. Estimation of the LOGSE effect on Numeracy and Literacy, according to variables of implementation and specification of the trend

	Trends									
	3 Periods: - 1945 to 1975 - 1976 to 1983 - 1984 to 1995		**2 Periods:** - 1945 to 1975 - 1976 to 1995		**2 Periods:** - 1945 to 1983 - 1984 to 1995		**1 Period:** - 1945 to 1995			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Numeray										
ESO1	-14.8***	-6.6	-15.2***	-2.4	-12.8***	-4.6	-13.2***	-3.2	-4.7	-2.2
ESO2	-18.6***	-7.9	-18.8***	-6.1	-16.7***	-7.7*	-17.2***	-8.3**	-9.1**	-6.2
BACH_LOGSE	-18.2***	-7.0	-18.4***	-5.6	-16.7***	-7.3	-17.3***	-8.5**	-9.0**	-6.0
Literacy										
ESO1	-15.2***	-12.0*	-16.0***	-6.3	-11.7***	-4.4	-13.0***	-3.5	-3.7	0.5
ESO2	-18.3***	-13.6**	-18.7***	-11.6*	-15.2***	-7.4	-16.4***	-7.5**	-7.7**	-0.6
BACH_LOGSE	-17.8***	-12.3*	-18.2***	-10.8*	-15.2***	-7.3	-16.6***	-7.7**	-7.8**	-0.4

Note 1: *, ** and *** mean that the coefficient is significant to 10%, 5% or 1%, respectively.

Note 2: Standard errors have been omitted but have been calculated following the methodology of the PIAAC study, using 10 plausible values for each competence and 80 replications.

Note 3: The estimations control for the same covariables included in Table 7.2.

The LOGSE effect

The analysis seems to show that there is a negative relationship between the implementation of the LOGSE reform and scores obtained in PIAAC test. This means that those individuals who were most exposed to this educational system obtained worse results and therefore the reform was not successful in increasing the cognitive skills of the population. However, the sensitivity analysis shown in Table 7.3 makes us to be cautious about reaching a final conclusion since the importance of the effect and its significance varies depending on the functional specification of the effect of birth year and on the specific variable that is used to identify the LOGSE effect.

Since part of the LOGSE effect is identified by the variability in the rate of implementation between regions it is important that these differences are exogenous. In other words, if those regions with higher (lower) scores are those that have implemented reform more (less) quickly, then our results could be biased to some extent. To test this hypothesis we have considered, on the one hand, the mean score for cohorts born within the five-years period before the start of implementation of LOGSE (1971-1975) for each region and, on the other hand, the degree of implementation of the LOGSE for different regions at the middle of the process (cohorts born in 1981). We find a non significant correlation between these two variables (P-value equals to 0.46 and 0.5 for numeracy and literacy respectively). Therefore, our analysis is valid with regard to this respect.

In any case, these results complement those obtained by Felgueroso et al (2013) in claiming the need for a deeper analysis of LOGSE as new opportunities arise through the research resources available. In this sense, it would be very useful if the statistics offices and research organizations set up specific measures to make the analysis of different education systems easier and more direct. One such measure could be the inclusion in the survey questionnaires specific questions which allow us to identify the educational law under which the surveyed individuals studied.

THE COMPETENCES AND AGE

This second part of the analysis is focused on the development of numeracy and literacy skills with age. Several factors can affect the passage of time and the maintenance of skills. We consider the employment status, the use of numeracy and literacy, and finally formal education.

Methodology

To estimate the effect of different factors on the depreciation of skills over the lifespan we estimate the age-*skills curve* using a quadratic specification and include the factor that we want to analyze in the estimation. Specifically we estimate the following equation:

$$y_i = \beta_0 + \beta_1 age_i + \beta_2 {age_i}^2 +$$

$$+\varphi_0 factor_i + \varphi_1 (age_i \times factor_i) + \varphi_2 \left({age_i}^2{}_i \times factor_i\right) + u_i \qquad (1)$$

Where y_i is the PIAAC score of individual *i* which depends on age_i, original and squared (indicating a quadratic trend). The estimated coefficients β_1 and β_2 give us the profile of the *age-skill curve* and β_0 is the constant of the model that indicates the starting point of this curve. The score can also be affected by a *factor* in two ways: the effect produced on the starting point captured by φ_0, and the effect it has on the profile or slope of the curve captured by φ_1 and φ_2. Finally u_i is a random error assumed with statistical properties required for estimating by OLS.

Therefore, with the estimation of model (1) the following two interesting hypotheses can be tested:

I. Ho: $\varphi_0, = 0$. The rejection of this would tell us that the starting point of the curve changes with the factor.
II. Ho: $\varphi_1 = 0$ o Ho: $\varphi_2 = 0$. The rejection of either of these two hypotheses would lead us to the conclusion that the factor also affects the rate of depreciation of human capital or, in other words, the slope of the *age-skill curve*.

Results

Table 7.4 includes the results of the separate consideration of four factors: the employment status (A); the use of numeracy and literacy at work (B) and at home (C); and formal education (D). In the first place, model (A) includes the employment status as a factor distinguishing between employed and non-employed (unemployed and inactive). The results show that for numeracy and literacy there is no effect on the starting point since the *Employed* variable has a non significant coefficient. Given that the age variable is included as differences with respect to 16, the starting point is the score for that age group. However, being employed is estimated to affect to the rate of depreciation of human capital. Specifically the positive coefficient of *Age×Employed* indicates a lower depreciation or even a gain in numeracy and literacy skills with age. Regarding the negative coefficient of *Age2×Employed* it means that depreciation is higher for the employed as age increases. The differences in the *age-skill curve* according to employment status can be seen in Graph 7.4 which shows the scatter plot formed by the representation of average score for each age group.[4] The adjustment of the scatter plot based on the estimation of model (A) in Table 7.4 is also shown. For the two disciplines the same pattern of adjustment lines is observed whereby the Employed and Non-Employed have the same starting point but have a different evolution: in the early years both groups tend to improve their competences, however the improvement is much higher and persistent for the Employed group. This means that the Non-Employed group starts losing skills at an earlier age. However, once they reach older ages, between 40 and 45 years old, the Employed group depreciates at a higher rate so that the two groups arrive at 65 years with a similar skill level.

Even though these results are those of a descriptive analysis, they are interesting if we consider the possible causal relationships implied. For example, although it may be that ability determines whether an individual is Employed or not (and not the other way around), we can hardly argue that ability affects the probability of being Employed differently according to age. Thus, it appears that there is some causality in the direction assumed in the estimation in Table 7.4, i.e. work activity affects the development of skills through age. Skills tend to decline over time even for those who are Employed. Jimeno et al. (2013) conducted a more detailed analysis of the effect of work experience in the maintenance of cognitive skills and find that it only has a positive effect for low skilled workers (primary education). Therefore, the beneficial effect of working is even higher for this group.

We have also analyzed the usage of skills distinguishing between when it happens in the work place and when it happens at home. We distinguish between the estimations for numeracy, in which case the usage of maths skills is taken into consideration, and literacy, in which case we are interested only in the usage of that competence. For the generation of the variables a series of questions from the PIAAC survey were taken into account, in which individuals respond to the frequency of usage of:

[4] In the graphs shown in this section we exclude those individuals who are studying because they represented a large group in the case of the Non-Employed group, thus distorting differences by employment status. This is treated in econometrics analysis including a dummy variable indicating whether the individual is still studying.

- In the case of numeracy: calculating budgets; percentages; using a calculator; doing algebra; advanced maths.
- For literacy: reading guides or instructions; reading or writing letters or emails; reading the newspaper; reading books manuals, invoices, maps; writing reports; filling out forms.

The possible responses in all these cases are five categories depending on the frequency of usage, from "never" to "every day". To construct the usage index we assigned the value 1 to the lowest category and 5 to the highest and we compute the average of all responses for each individual. Finally we have a variable of use at work and at home, for numeracy and literacy separately. For the estimation of models (B) and (C) in Table 7.4 this variable is categorical, distinguishing between two groups, high and low usage, split by the median value.

Those who have a high use of the competences obtain higher scores from the starting point (16 years). For example, in the case of high usage at home, numeracy skills increase by 13.5 points. This happens in the same way for the case of the use of literacy, both at home and at work. Only in the case of the use of numeracy at work it does not seem to have a significant effect for younger individuals. Also the usage of competences seems to affect the rate of depreciation, this is given by the significance of the variables interacted with *Age*: Age× Use_work and Age×Use_home. Both in numeracy and literacy this coefficient is positive indicating a lower depreciation at early ages. On the other hand, a negative coefficient for usage at home is estimated, when interacting with *Age2*, indicating that for advanced ages the rate of depreciation is higher.

Table 7.4. Estimation of the age-skill curve for Numeracy and Literacy

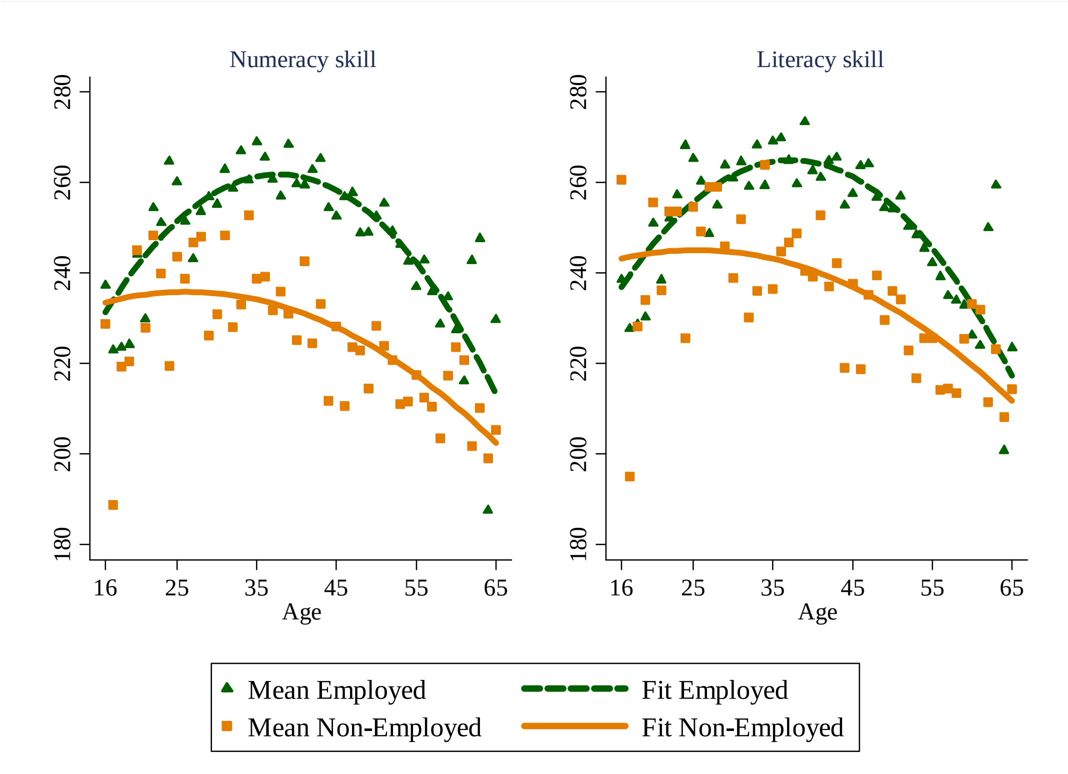
VARIABLES	Numeracy (A)	Numeracy (B)	Numeracy (C)	Numeracy (D)	Literacy (A)	Literacy (B)	Literacy (C)	Literacy (D)
Age	4.2	17.9***	-3.3	7.7*	3.8	10.8***	-7.4*	5.6
	(2.8)	(5.1)	(4.5)	(3.6)	(2.8)	(4.0)	(4.2)	(4.2)
Age 2	-2.2***	-5.0***	-0.6	-2.5***	-2.1***	-3.6***	0.3	-2.0**
	(0.6)	(1.0)	(0.8)	(0.7)	(0.6)	(0.8)	(0.8)	(0.8)
FACTORS:								
Employed	-2.4				-6.5			
	(4.3)				(4.5)			
Age x Employed	23.9***				22.7***			
	(4.2)				(4.3)			
Age3 x Employed	-4.3***				-4.1***			
	(0.9)				(0.9)			
Use_work		1.5				16.9**		
		(7.3)				(7.1)		
Age x Use_work		15.3**				10.3*		
		(6.5)				(6.1)		
Age2 x Use_work		-2.0				-1.3		
		(1.3)				(1.2)		
Use_home			13.5**				19.0***	
			(5.8)				(4.4)	
Age x Use_home			13.7**				16.6***	
			(5.8)				(4.4)	
Age2 x Use_home			-2.4**				-3.2***	
			-110				(0.9)	
Sec. 1st stage				29.0***				25.5***
				(4.7)				(5.7)
Sec. 2nd stage				47.3***				44.4***
				(5.0)				(5.6)
University (3 years)				54.4***				53.2***
				(8.0)				(9.2)
University (5 years)				73.7***				74.0***
				(8.9)				(10.0)
Constant	234.0***	234.1***	227.7***	206.0***	243.6***	239.3***	236.8***	217.1***
	(3.0)	(5.6)	(5.2)	(5.4)	(3.1)	(4.6)	(4.6)	(5.2)
Observations	5,93	3,367	2,563	5,93	5,93	3,367	2,563	5,93
R2 (%)	17	16	22	37	16	24	27	37

Note 1: *, ** and *** mean that the coefficient is significant to 10%, 5% or 1%, respectively.

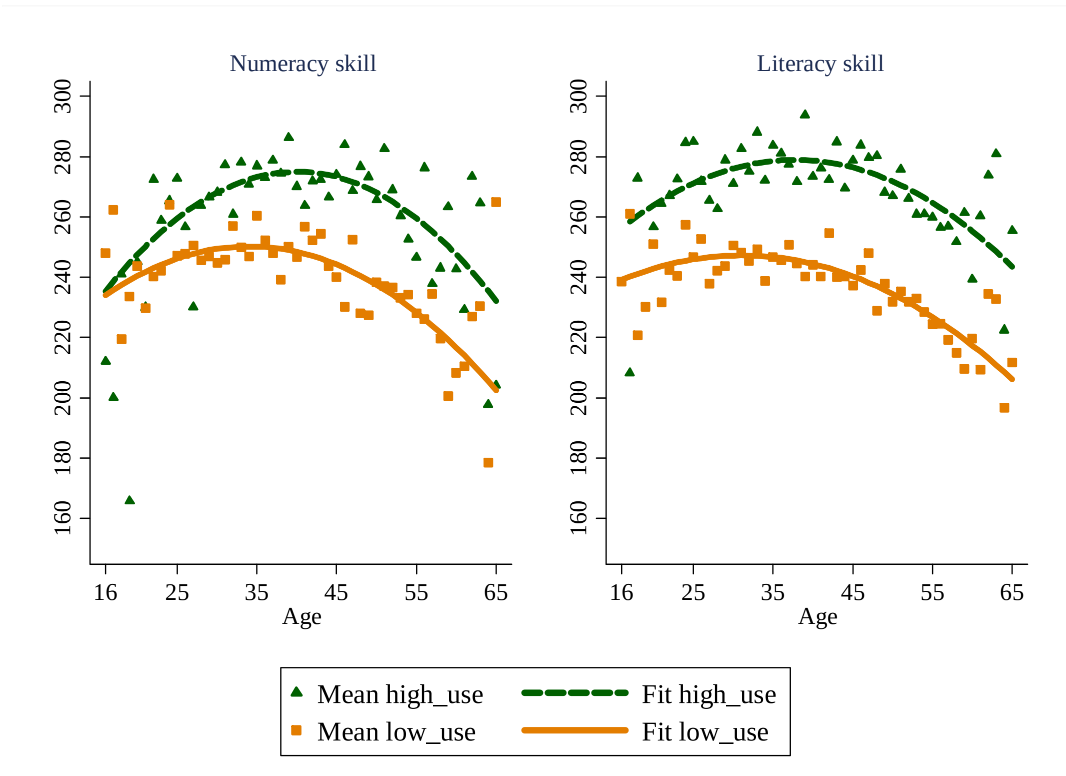
Note 2: Standard errors are shown in brackets and have been calculated following the methodology of the PIAAC study, using 10 plausible values for each competence and 80 replications.

Note 3: All models control for a binary variable indicating whether the individual is still studying, which has been omitted because it has no interest in this analysis. Also for model (D) education variables interacted with age are included, although they are not shown due to lack of significativity.

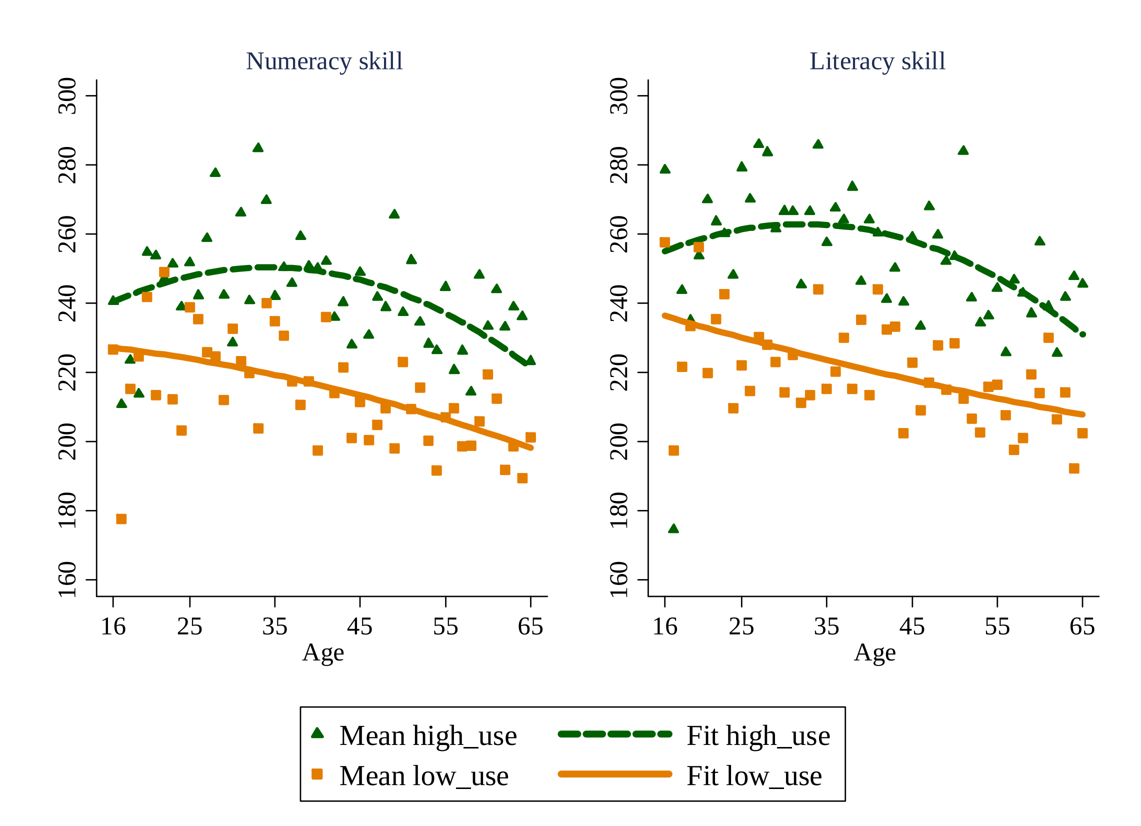
Graph 7.4. Age-Skill curve by Employment Status



Graph 7.5. Age-Skill curve for Employed individuals by use of numeracy and literacy at work



Graph 7.6. Age-Skill curve for Non-Employed individuals by use of numeracy and literacy at home



The estimated effects can be better visualized graphically. In Graph 7.5 we can see the evolution of skills for those who are employed by usage at work. For the two disciplines assessed the lines of adjustment indicate that those with high usage tend to improve their skills with age and this improvement continues reaching the peak of skills at a more advanced age. After that peak this group continues having better scores for all age groups. The inactive and unemployed individuals are represented in Graph 7.6. Differences of the age-skill profile appear to be even more remarkable. The adjustment line for those who are Non-Employed and also have a low usage of skills at home has a negative slope at every age group. This means that these individuals depreciate skills from the very beginning of the *age-skill curve*. By contrast, the inactive and unemployed individuals who do use maths at home have a better evolution from the beginning and depreciate at a slower rate for older ages. But the process seems to be reversed to some extent and their skills tend to fall quicker for advanced ages.

Finally, we estimate model (D) in which we look at the effect of formal education on the age-skill profile. In this case we only show the effect of the different levels of education on the starting point of the curve due to the fact that education interacted with *Age* and *Age2* was not significant, indicating that there are no differences in the rate of depreciation between different educational levels. Therefore, the effect of education seems to be the same for all age groups with no significant differences in the slope of the curve. However, the effect of education is much higher than any of the other factors analyzed. For example, the effect of going from primary or no education (reference group in model D) to university education (5 years) is about 74 points in numeracy. In the same discipline other factors do not reach more than 40 points of difference for age groups between 35 and 45 years (see Graphs 7.4, 7.5 and 7.6). In Graph 7.7 we can see the differences between each educational level. It is can be observed that the adjustment lines are vertical displacements and more or less parallel. Note that this result is based on absolute comparisons and is therefore consistent with the result in Villar (2013) that relative skills of university educated individuals improve over time with respect to individuals with basic education.

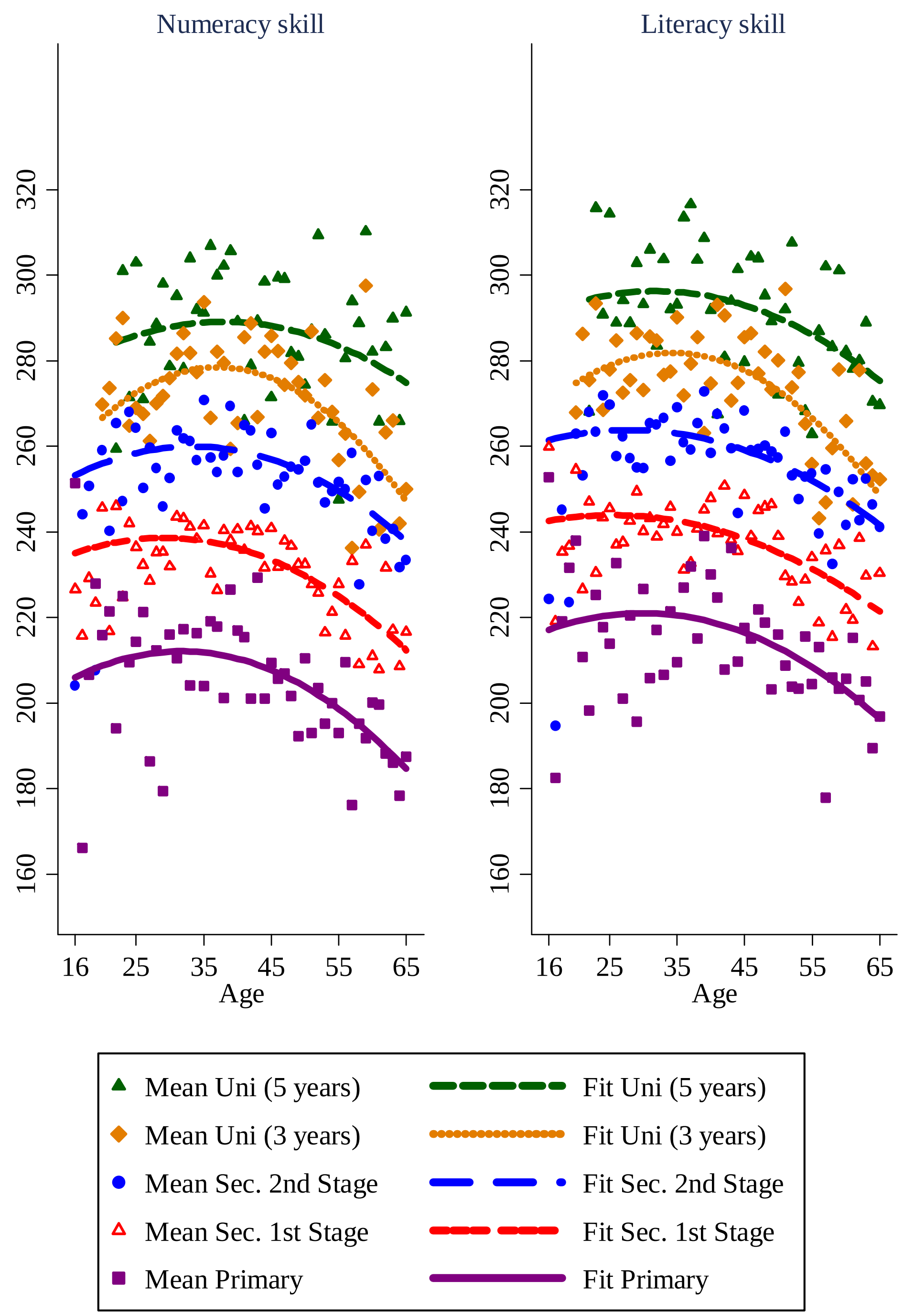
Implications

Among the factors analyzed the employment status seems to have higher effect on the rate of skills depreciation. In fact after 16 years old the *age-skills curve* has a very high positive slope for those who are employed compared to those who are unemployed or inactive. This means that work activity acts as a beneficial factor for the development of the skills. Therefore, the importance of being employed is not only because of the production of goods and services that a person produces but because of his/her own ability to produce (productivity) is increased. Symmetrically, the loss that occurs when a person is not working is also twofold: he/she stops producing and loses skills to produce. In this sense it is worrying that precisely younger individuals face higher unemployment rates. The assessment of employment policies which result in an eventual promotion of employment for older groups to the detriment of youth employment could show these types of effects. Precisely an example of this type of policy is the delay of retirement age that could result in increased unemployment for young people and therefore a delay in labor market entrance and loss of skills.

Regardless of whether an individual works or not, the use of numeracy and literacy allows skills to be maintained for longer and the depreciation of human capital is delayed. In this case, the relevant policies are those related to investment in human capital and the matching of individuals' skills and jobs. In a scenario in which the skills are not going to be used at work the investment in education may turn out to not be so profitable.

Finally, we may conclude that the eventual depreciation of human capital is a general phenomenon. The loss of cognitive skills for older ages occurs regardless of whether the individual is employed or not, uses skills or not, and this happens for all educational levels. In a context where developed economies are suffering from ageing of the workforce, whether because of the demographic structure or because of the extension of retirement age, there are potential serious consequences for the productive structure.

Graph 7.7. Age-Skill curve by educational level



GENERAL CONCLUSIONS

After carrying out the analyses we can summarize the following general conclusions:

- The numeracy and literacy skills tend to be higher for young cohorts, having a maximum at age group 25-35 (born within 1985-75). This general result is in line with the results of previous international studies conducted in other countries.
- The relationship observed between age and skills is due to different factors that are mixed with the age effect and cohort effect. The age effect refers to changes in the cognitive skills as a result of biological maturity and the experiences that an individual accumulates as a consequence of living longer. In contrast, the cohort effect is related to factors that affect a person for having been born in a specific year.
- There seems to be an anomaly in the form of a trend change in the relationship between numeracy score and age, begining for those born in 1976 (see Graph 7.2). Indeed, this change in trend coincides with the first cohorts educated under the new LOGSE law.
- The identification of the probability of being educated under the LOGSE system has allowed us estimating a negative effect on numeracy and literacy skills, although the significance of this effect varies with the specification of different trends.
- The analysis of the *age-skill curve* according to employment status or usage of skills at work and at home suggests that accumulated experiences have a real effect on how competences evolve with age.
- Cognitive skills seem to be developed for longer for those individuals who work and those who use numeracy and literacy in the workplace or at home. Therefore life experiences affect the rate of depreciation of human capital.
- However, the eventual depreciation of human capital for older cohorts seems to be a general phenomenon that occurs regardless of the life experiences that individuals develop.

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8. Education and cognitive skills in the Spanish adult population. Intergenerational comparison of mathematical knowledge from the PIAAC data

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8. EDUCATION AND COGNITIVE SKILLS IN THE SPANISH ADULT POPULATION. INTERGENERATIONAL COMPARISON OF MATHEMATICAL KNOWLEDGE FROM THE PIAAC DATA

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ABSTRAC

This study analyzes the results of the PIAAC tests for Spain in the field of *mathematical competence*, by comparing the relative worth of the skills acquired by the different generations that compose the Spanish working age population. This comparison takes into account the complete distributions of the population of the different cohorts in the five levels of competence defined by PIAAC, applying the methodology from Herrero and Villar (2012), which allows for comparison of qualitative variables. . The evaluation of a group thus obtained is a measure of the probability that this group "dominates" other groups, in the sense that an individual picked at random from this group will have a level of competence above an individual randomly selected from any other group. The results show different behaviours for the different cohorts depending on their educational achievement.

Key words

Intergenerational comparison, qualitative variables, educational achievement, cognitive skills, PIAAC.

INTRODUCTION

Background

The *Programme for the International Assessment of Adult Competences* (PIAAC), coordinated by the OECD, is a new step in the generation of internationally comparable data on the cognitive skills of the population in a wide range of countries. It extends former work on the abilities of the adult population in the field of reading literacy (IALS, ALL) and complements the studies carried out on the levels of competence of young people in different fields and for different ages (PISA, PIRLS and TIMSS, among others).[1] The present study provides cross-section data on the skills of the adult population (aged 16 to 65 years) in the areas of *reading literacy* and *mathematics.* Twenty-four countries have participated in this first wave and a few more will be incorporated in an extension intended for the next years. The assessment of people's skills is carried out through questionnaires and the valuations are measured on a scale of 0-500 points.

The key aim of this new database is that of enabling a better understanding of the relationship between education, acquisition of cognitive skills and the ageing of the population. Those are relevant aspects for personal fulfilment, the accumulation of human capital, the dynamics of the job market, and the development of societies. This study expands substantially the available evidence on those matters and will thus facilitate the design of effective policies to enhance people's skills and to support their development and implementation in different countries (see OECD (2012, 2013) for a discussion).

There is broad range of empirical evidence that shows that investing in expanding the skills of the population is the best recipe for transforming scientific and technological development into growth and welfare (see for example, Acemoglu & Robinson (2012)). The acquisition of those skills is closely linked to both formal education and experience (Desjardins (2003), Statistics Canada & OECD (2000), (2005)). For this reason, the provision of formal education and a suitable integration into the labour market are key for the development of people's skills. One has to bear in mind that the worth of those skills tends to decrease over time, their under-utilization or their lack of use, and the mismatch that may derive from changes into the individuals' environment (Pazy (2004), Staff et al. (2004), De Grip et al. (2005)).

Cognitive skills, ageing of the population and demographic structure

There is a well-defined pattern of the evolution of cognitive skills. Theoretical and empirical studies show that there is a negative correlation between cognitive skills and age. This

1 IALS: International Adult Literacy Survey. ALL: Adult Literacy and Lifeskills Survey. PISA: Program for International Student Assessment. PIRLS: Progress in International Reading Literacy Study. TIMSS: Trends in International Mathematics and Science Study. The first three studies are coordinated by the OECD whereas the last two by the International Association for the Evaluation of Educational Achievement.

phenomenon, which is observed in cross-section and longitudinal studies, is compatible with the existence of different pathways, depending on the type of the cognitive skill being considered. All cognitive skills seem to increase up to the ages of 18 or 20 years; soon after the decay starts in some types of cognitive skills while others decrease later on. Be as it may, they always end up by diminishing at older ages (see Desjardins & Warnke (2012) for a fuller discussion).

The dynamics of the cognitive skills are very complex because they involve individual and social aspects. The individual aspects are associated with processes of neuronal and behavioural maturation (the latter resulting from the accumulation of knowledge, the effect of use –experience- and from the individual's interaction with a changing environment throughout his/her life). There are also changes in the social context that affect in different ways the experience of the cohorts present at any given point in time (the so-called *cohort effects* and *period effects*).[2] All of this may alter the pattern of individual and collective interactions associated with the evolution of cognitive skills.

As a result, the analysis of the relationship between cognitive skills and demographic structure turns out to be complex, especially as there is a wide range of cognitive skills whose patterns of behaviour differ over time (e.g. *fluid* skills vs *crystallized* skills, *basic* skills versus *fundamental* skills). In particular, cross-section studies must be interpreted carefully because of the ageing effect being mixed up with cohort effects that can be important.[3] Such studies, however, are suitable for analyzing the differences that exist between individuals of different ages at a point in time and they are relevant from the perspective of public action (see Schaie (1996), (2009)).

The study of the cognitive skills across generations in a given country is particularly important right now for several reasons. Firstly, because of the effect of the economic recession that has generated levels of unemployment unknown for decades, especially among the young, which leads to a very rapid loss of the educational investment. Secondly, because of the progressive ageing of the working population associated with an increase of life expectancy and the delay in the retirement age. And thirdly, because of the impact of human capital endowments on the distribution of income and employment.

Aim of the study

In this study we analyze the results of the PIAAC tests for Spain in the field of *mathematical competence*, by comparing the relative worth of the skills acquired by the different generations that compose the Spanish working age population.

[2] *Cohort effects* are related to some structural changes that affect the development of cognitive skills of some cohorts in relation to others (eg: the extension of compulsory education). *Period effects* refer to events that occur at a certain point in time and affect all cohorts simultaneously.

[3] Desjardins & Warnke (2012) propose the use of sequences of cross-section studies as the best alternative, given the scarcity and small size of the samples of the available longitudinal studies. In their study they carry out an exercise comparing results of IALS and ALL for a set of nine countries, with the aim of later incorporating those from PIAAC. Unfortunately Spain did not participate in the earlier IALS and ALL studies, so that this strategy of analysis is not available for our country.

Although the PIAAC data refer to both reading literacy and mathematics, we have chosen the mathematical competence because it is perhaps the most relevant novelty of that study, since there were already different assessments of adults' reading competence (e.g. IALS and ALL). It is also a type of cognitive skill in which the effect of ageing might be more significant, since some of the language skills seem to increase through use and context up to relatively advanced ages.

Mathematical competence is defined as the ability "to access, use, interpret and communicate mathematical information and ideas in order to relate and manage mathematical situations found in adult life. This involves managing situations or resolving problems in real contexts, responding to ideas, information or mathematical content represented in different ways."

PIAAC defines six ***levels of competence***, parameterized by certain thresholds of the test scores. Table 8.1 shows those thresholds and describes the elements that characterise each level. Note that the setting of the levels is essentially qualitative (i.e. the levels are defined in terms of the tasks that individuals are able to perform) and then it is made operational through a convenient parameterization.

Table 8.1. Description of performance levels in mathematics with corresponding score intervals

Level	Types of tasks successfully completed in each performance level
Below level 1 ***Less than 176***	Tasks at this level require the interviewee to perform simple processes such as counting, sorting, performing basic arithmetic operations with whole numbers or money, or to recognize common spatial representations in specific and familiar contexts where the mathematical content appears explicitly with little or no text or distractors.
1 ***176 – 225***	Most of the tasks in this level require the interviewee to perform basic mathematical processes in common and specific contexts in which the mathematical content appears explicitly with little text or distractors. The tasks to be performed usually require simple processes such as counting, sorting, performing basic arithmetic, understanding simple percentages like 50%, and locating and identifying elements or simple spatial or graphic representations.
2 ***226 – 275***	At this level the interviewee is required to identify and manage information and mathematical ideas within a range of common contexts in which the mathematical content is visually or explicitly presented with relatively few distractors. The tasks usually require the application of two or more steps or processes that involve calculation of decimals with one or two graphs, percentages and fractions; simple measurements and spatial representation; estimation; and interpretation of data and relatively simple statistics in texts, tables and graphs.
3 ***276 – 325***	The interviewee is required, at this level, to understand a wide range of mathematical information that may be complex, abstract, or may be found within unfamiliar contexts. These tasks require several steps and may involve problem-solving strategies and relevant processes. Tasks will include the application of the concepts of number and spatial sense; recognition and work with mathematical relations, patterns, and numerically and verbally expressed proportions; and the interpretation and analysis of basic data and statistics in text, tables and graphs.
4 ***326 – 375***	At this level the interviewee must understand a wide range of mathematical information that may be complex, abstract or be included in unfamiliar contexts. For these tasks it is necessary to perform multiple steps and choose relevant processes and strategies of problem solving. The tasks tend to require a more complex level of analysis and reasoning about quantities and data; statistics and probability; spatial relations; and change, proportions and formulas. At this level it may be necessary to understand formulations or formulate explanations for the answers or choices.
5 ***376 – 500***	Tasks in this level require the interviewee to understand complex mathematical representations and ideas as well as abstract and formal statistics, possibly included in complex texts. Interviewees may possibly have to integrate multiple types of mathematical information which require translation and interpretation; draw inferences; develop or work with mathematical models or arguments; and justify, evaluate and critically reflect on solutions or choices.

Source: PIACC (2012)

Our goal here is to carry out an intergenerational comparison of cognitive skills of the Spanish adult population in the field of mathematics. The main novelty of our analysis, besides the database, is the use of the complete distributions of the population of the different cohorts in the five levels of competence defined above. Our approach involves, therefore, going beyond the comparison of mean values and exploiting the information contained in the simplified version of the density provided by the distribution the cohorts through competence levels. To do so we apply the methodology of Herrero & Villar (2012), which allows the comparison of categorical variables between different population groups. The evaluation of a group is a measure of the probability that this group “dominates” other groups, in the sense that an individual picked at random from this group will have a level of competence above an individual randomly selected from any other group. We describe the evaluation procedure in

Section 2. We shall see that the evaluation so obtained differs substantially from the comparison of the average values of the test.

Each cohort will be divided into three groups according to their educational achievements (compulsory education, secondary education and university studies), in order to perform the comparative analysis. We shall use the term "educational achievements", instead of the more usual "education levels", in order to preserve the term *level* for the six "competence levels" in Table 8.1 and so avoid confusion.

THE EVALUATION PROCEDURE

We address the comparison of the cognitive skills of the different cohorts using the model developed in Herrero & Villar (2012) for the relative evaluation of groups in terms of categorical variables. That approach is related to the statistical analysis of similarity between orderings and to the sociological and economic literature regarding comparative assessments in different contexts (e.g. Lieberson (1976), Reardon & Firebaugh (2002), Laslier (1997), Palacios -Huerta & Volij (2004)).

We focus on the Spanish working age population, which will be divided into five different cohorts. Each cohort is then sub-divided into three different sets, according to the educational achievements of its components. From this configuration we will analyze the distribution of each of the resulting groups (defined by cohort and educational achievement) in terms of the *five* competence levels defined by PIAAC.[4]

The evaluation model

The basic idea is as follows. We have a population divided into a set of g groups (the fifteen resulting from five cohorts and three educational achievements, in our case). The individuals' outcomes (PIAAC test results) can be classified into s categories (five competence levels), ordered from best to worst. Let a_{ir}, $i = 1, 2, \ldots, g$, $r = 1, 2, \ldots, s$, denote the share of individuals in group i in the r category.

We say that group i ***dominates*** group j when it is more likely that picking at random an individual from group i she belongs to a higher category than that of another individual randomly chosen from group j. The probability that an individual from group i dominates another from group j, p_{ij},, is calculated as follows:

$$p_{ij} = a_{i1}(a_{j2} + \ldots + a_{js}) + a_{i2}(a_{j3} + \ldots + a_{js}) + \ldots + a_{i,s-1}a_{js} \quad [1]$$

From here we can define the relative advantage of group i with respect to group j, RA_{ij}, as follows:

[4] PIAAC actually defines six levels, from below 1 up to 5; yet there is in only one entry in level 5 with too few observations so we have aggregated levels 4 and 5 without loss of generality.

$$RA_{ij} = \frac{p_{ij}}{\sum_{k \neq i} p_{ki}}$$

The relative advantage of group *i* with respect to group *j* is nothing more than the probability that group *i* dominates group *j* divided by the sum of the probabilities that group *i* be dominated by some other group.

To obtain an overall evaluation of group *i* in society, we take a weighted sum of its relative advantages with respect to all other groups. That is, the relative advantage of the group *i* is given by:

$$v_i = \sum_{j \neq i} \lambda_j RA_{ij}$$

Since the weights reflect the relevance of the different groups, it is only natural to choose them consistently with their own evaluation, i.e. taking $\lambda_j = v_j$. In this way, each group enters the evaluation of the relative advantage of the others with the weight corresponding to its own relative advantage. This implies that we have to find a vector $\mathbf{v} = (v_1, v_2, ..., v_g) > \mathbf{0}$ such that:

$$v_i = \sum_{j \neq i} v_j RA_{ij} = \frac{\sum_{j \neq i} v_j p_{ij}}{\sum_{k \neq i} p_{ki}}, \quad i = 1, 2, ..., g \, [2]$$

Herrero & Villar (2012) prove that this vector always exists, is strictly positive and unique (once normalized) and that it can be easily calculated since it corresponds to the dominant eigenvector of the following matrix:

$$Q = \begin{bmatrix} g-1-\sum_{i \neq 1} p_{i1} & p_{12} & \cdots & p_{1g} \\ p_{21} & g-1-\sum_{i \neq 2} p_{i2} & \cdots & p_{2g} \\ \cdots & \cdots & \cdots & \cdots \\ p_{g1} & p_{g2} & \cdots & g-1-\sum_{i \neq g} p_{ig} \end{bmatrix} [3]$$

The off-diagonal elements of the *Q* matrix are the pair-wise dominance probabilities p_{ij}. The elements on the diagonal tell us the probability that a randomly chosen individual from group i belongs to a category that is not worse than a randomly chosen individual from any other group. Is easy to see that the matrix *Q* is a Perron matrix whose columns add up to (g - 1). From this it follows (see for instance Berman & Plemmons (1994)) the existence, positivity and uniqueness (when *Q* is irreducible) of the **v** vector whose components satisfy equation [2].

Application to our problem

The problem that we want to address here is the comparative evaluation of human capital accumulated by the different cohorts, in the field of mathematics. For this we are going to use the information on the distribution of PIAAC test results for each cohort and educational achievement in the five competence levels defined. Our reference groups will, therefore, be different ***cohorts by educational achievement***. We have considered five cohorts: population of 24 years old or less, population between 25 and 34 years old, population between 35 and 44 years old, population between 45 and 54 years old, and population of 55 years old or more. And three educational achievements: compulsory education, secondary education, and university studies.[5] The categories correspond to the above-mentioned five competence levels: below 1, 1, 2, 3 and 4 plus 5.

Thus, we will have a *Q* matrix (as in equation [3]) of 15 by 15 entries, which generates an eigenvector of fifteen components. This eigenvector provides an estimate of the relative quality of the human capital in the different cohorts in the field of mathematical competence, where each cohort with a given educational achievement is compared with all the other cohorts with their corresponding educational achievements. Since the eigenvectors have a degree of freedom, we will choose the normalization that makes the first component of the eigenvector equal to one. We measure, therefore, the value of each cohort in terms of the value that it represents over the youngest cohort with the lowest educational achievement. We will refer to this context as ***the joint evaluation.***

From this joint evaluation we will carry out two additional assessment exercises. First, trying to identify the intergenerational profile of those cohorts with the same educational achievements. Second, trying to isolate the impact of intermediate and higher education on the evaluation of each cohort.

To analyze the impact of ageing on cognitive skills, we re-normalize the values of the eigenvector by making the worth of the youngest cohort for each educational achievement equal to one. The resulting values provide a measure of the quality of human capital of each cohort relative to the other cohorts with the same education, in units corresponding to the value of the youngest generation. We will refer to this context as a ***separate evaluation by educational achievements***.

To analyze the impact of secondary and university education on the evaluation of the different cohorts, we will compare groups of the same age, making the value of all the cohorts with compulsory education equal to one. In this way we compare the variation of the quality of human capital due to the increase in education, in terms of the value of compulsory formation for each age group. We will refer to this context as the ***separate evaluation by age***.

[5] As the study refers to a set of generations that have experienced diverse educational systems, it should be clarified that by compulsory education we mean those individuals who have achieved, at most, the equivalent of the current compulsory education (up to age 16). We include in secondary studies all those who have reached the current level of baccalaureate (or equivalent professional training). In university education we include both the individuals who have done a five year degree (long cycle), a three year degree (short cycle) or the most recent of four years, as well as the equivalent professional training.

RESULTS

Population distribution by competence levels and joint assessment of the cohorts by educational achievements

Table 8.2 provides complete information on the distribution of cohorts in the different levels of mathematical competence, according to their educational achievements. This is the basic information for constructing the *Q* matrix of equation [3] according to the formula [1].

Table 8.2: Distribution of the different cohorts in the five competence levels by educational achievements (%)

Cohorts	Competence leves (mathematics)					
	4	3	2	1	< 1	Accummulated
Compulsory education						
24 or less	0.29	18.62	50.53	23.01	7.56	100
25-34	1.25	13.42	43.08	28.51	13.74	100
35-44	0.23	10.85	48.66	28.18	12.08	100
45-54	0.31	7.52	39.66	35.67	16.85	100
55 or more	0.00	3.74	30.41	36.34	29.50	100
Secondary education						
24 or less	3.85	41.36	45.13	8.68	0.98	100
25-34	2.91	32.25	47.09	16.43	1.31	100
35-44	2.45	35.25	44.28	14.83	3.19	100
45-54	2.87	22.98	56.91	14.64	2.60	100
55 or more	1.35	14.84	56.61	23.53	3.67	100
University studies						
24 or less	16.30	41.24	40.95	0.19	1.33	100
25-34	11.82	50.73	34.05	3.40	0.00	100
35-44	10.01	54.55	31.67	2.64	1.13	100
45-54	12.56	47.53	32.19	6.36	0.98	100
55 or more	5.30	35.31	44.23	14.72	0.44	100

NB: The data on each cohort by educational achievement is obtained by elevating the sample data to the level of the population, using the corresponding elevation coefficients.

The data show that the larger proportion of the population with compulsory education lies in competence level 2, except for the oldest cohort in which most have level 1. There is a broad representation of the population with this education below level 1, especially for the oldest cohorts, while there is practically no participation at level 4. The larger fraction of the population with secondary studies is also situated at level 2, but now there is a significant part of the population in level 3, more so the younger the cohort is. Level below 1 is almost empty in all age groups and level 1 is not very important, except for the oldest population. Finally, in the population with university education level 3 clearly prevails, except for the cohort of 55 or more where level 2 is majoritarian. Level 1 is not very important, except for the oldest cohort, while level 4 has a broad representation, especially in the younger cohorts.

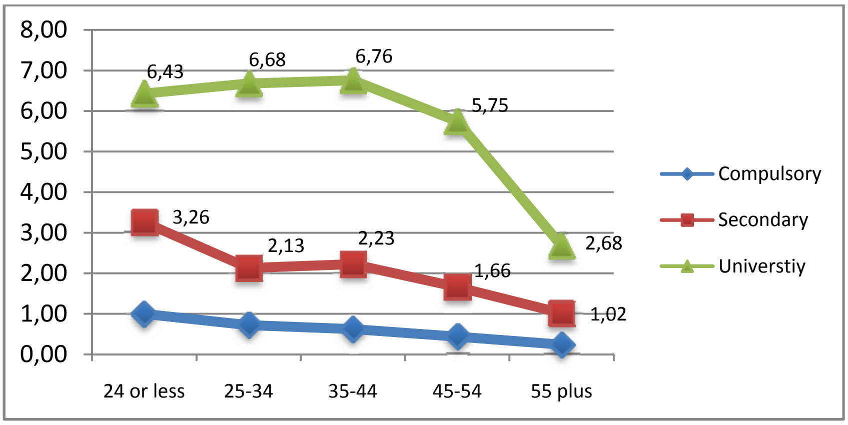
From a formal point of view getting an evaluation of the different cohorts amounts to transforming the matrix of 75 values in Table 8.2 into a vector of fifteen components that describes the relative position of each group according to the domination probabilities. This form of valuation of the groups takes into account the distributions at different competence levels of the individuals, depending on the cohort they belong to and on the educational achievement

The resulting evaluation provides a measure of the relative quality of human capital in the field of mathematical competence. To properly interpret the results presented below we should bear in mind that we have normalized this measure so that the value of the youngest cohort with the lowest education is equal one. Therefore, each value is expressed in this type of units.

The results of the joint evaluation of the different cohorts by educational achievements, Graph 8.1 and Table 8.3 (A), show that:

- Within each cohort the group with university studies has a much higher value than that with secondary studies, and the latter has a value clearly higher than the group with compulsory studies.
- The groups with university studies dominate all the others, except the oldest group with respect to the younger group with secondary studies.
- The values tend to decrease with age for all educational achievements. The difference between the youngest cohort and the oldest is very large, but the reduction path is not uniform.
    - The joint evaluation of the groups with compulsory education shows a moderate reduction, steadily decreasing with age.
    - The joint evaluation of the groups with secondary education drops substantially from the first to the second cohort before slightly recovering and then dropping moderately.
    - The joint evaluation of the groups with university studies presents a profile slightly increasing for the first three cohorts, dropping noticeably in the fourth and very prominently in the last.

Graph 8.1.- Joint evaluation of the cohorts by educational achievements



This evaluation of the cohorts differs clearly, regarding the relative magnitudes, from the one that would be obtained by associating the average value of the PIAAC tests to each cohort and educational achievement. Table 8.3 (B) sufficiently illustrates this difference (in it we have also normalized the average values by setting equal to one the average of the youngest cohort with lower education, in order to be able to make the comparison).

Table 8.3: Valuation of the cohorts according to formative stages and average values (normalized) of the tests

Education	**Cohorts**				
	24 or less	25-34	35-44	45-54	55-65
(A) Joint Valuation					
Compulsory	1.00	0.73	0.62	0.44	0.24
Secondary	3.26	2.13	2.23	1.66	1.02
University	6.43	6.68	6.76	5.75	2.68
(B) Normalized average values					
Compulsory	1.00	0.95	0.95	0.90	0.84
Secondary	1.12	1.09	1.08	1.06	1.02
University	1.19	1.19	1.20	1.18	1.11

Comparison of the cohorts by educational achievements: separate evaluation by educational achievements and separate evaluation by age

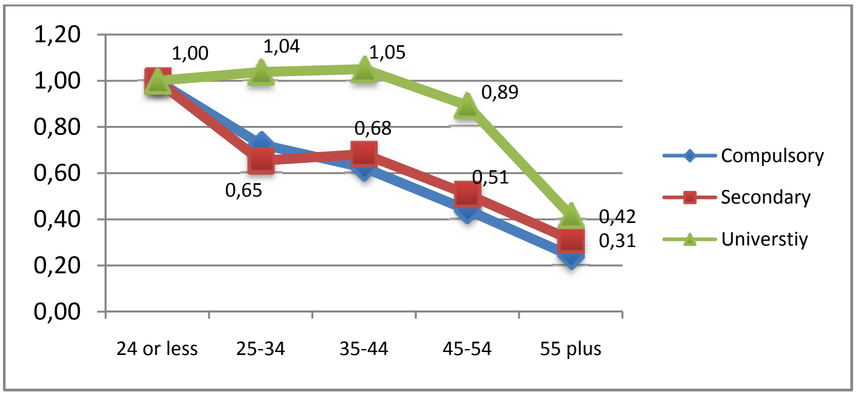
The joint evaluation presented in the previous section combines the effect of ageing and the effect of education. The separate evaluations that follow attempt to assess the importance of each one of these effects.

To carry out the ***separate evaluation by educational achievements*** (Graph 8.2 and Table 8.4 (A)), we make the value of the youngest cohort equal to one for each educational achievement. In this way we get an estimate of "the cost of ageing" in terms of cognitive skills, depending on the education. The data show a similar pattern in the population with compulsory and secondary education. On the one hand, the worth of the youngest cohort is well above the others. On the other hand, there is a very sharp drop in the worth of the second cohort with respect to the youngest one. This effect is corrected slightly in the third cohort for the case of secondary education, and then continues to fall sharply in the fourth and fifth cohorts.

The evaluation of the cohorts with university studies shows a different profile. Their worth increases for the first three cohorts, slightly decreases for the fourth one and then drops sharply for the oldest cohort. In addition, the dispersion of the values of the population with university studies is much lower than that of the rest.[6]

The loss of value of human capital between the youngest generation and the oldest one oscillates between 75% for the population with compulsory studies and 60% for the population with university studies. The relatively small difference of this depreciation between the cohorts is largely related to the sharp drop in the value of the older population with university studies.

Graph 8.2.- Separate evaluation by educational achievements



We now consider the ***separate evaluation by age*** in order to get an idea of the effect of education on each cohort. In this case we make the value of each cohort with compulsory education equal to one.

The data show that reaching secondary education translates to a value of between three and four times that of the compulsory education of each cohort, with an increasing impact with age (Graph 8.3, Table 8.4 (B)). This graph rises to values between six and a half and thirteen times in the case of university studies, with an increasing pattern until the fourth cohort before falling in the final one.[7] The graphic illustrates well that educational achievements substantially affect cognitive skills across generations.

[6] The coefficient of variation is 0.46 for the case of compulsory education, 0.41 for secondary education and 0.29 for university studies.

[7] The values of the ratios between university and intermediate education, from the youngest generation to the oldest, are the following: (1.97); (3.13); (3.04); (3.46); y (2.63).

Graph 8.3.- Separate evaluation by age

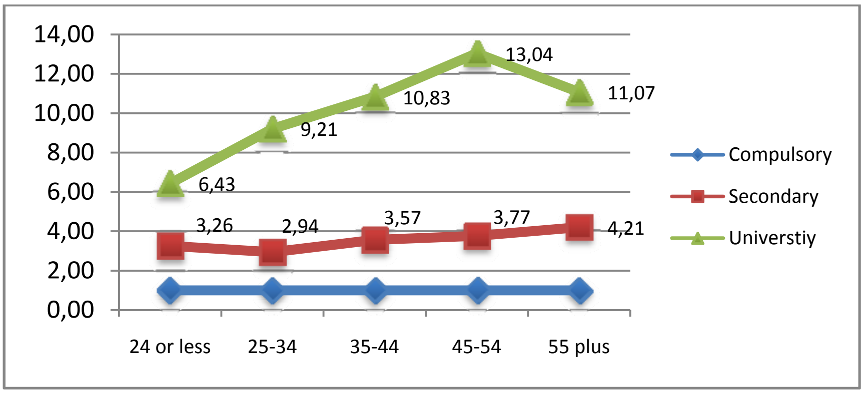


Table 8.4: Separate evaluation of the cohorts by educational achievements and by age

Education	Cohorts				
	24 or less	25-34	35-44	45-54	55-65
	(A) Separate evaluation by educational achievements				
Compulsory	1.00	0.73	0.62	0.44	0.24
Secondary	1.00	0.65	0.68	0.51	0.31
University	1.00	1.04	1.05	0.89	0.42
	(B) Separate evaluation by age				
Compulsory	1.00	1.00	1.00	1.00	1.00
Secondary	3.26	2.94	3.57	3.77	4.21
University	6.43	9.21	10.83	13.04	11.07

Discussion

Introduction

One of the most fundamental changes experienced by the Spanish society in the last decades has been the increase of the educational achievements. The average years of schooling of the Spanish population has been substantially enlarged due to three main causes. First, the extension of compulsory education from fourteen to sixteen years.[8] This implies that the population with "compulsory education or less" has a different composition in the younger and the older cohorts. Second, the wide proportion of children nowadays receiving early education (pre-schooling). There is evidence of the important role that early education has in the acquisition of cognitive skills in adulthood. And third, the expansion of non-compulsory education (particularly with respect to university studies). All those elements create a cumulative effect that modifies the composition of the different cohorts regarding educational achievements, by improving the relative situation of the younger cohorts with respect to the older ones.

[8] This change was introduced when the "Ley General de Educación" was substituted by the "Ley Orgánica de Ordenación del Sistema Educativo (LOGSE)", formally sanctioned in 1990.

There are also some cohort-specific effects due to the institutional features of the education system and the labour market. Those "cohort effects" affect the dynamics of cognitive skills by interacting with the effect of education and ageing. Regarding the educational system, there has been a number of changes in the structure of the studies, whose implementation may involve costs for those who experience them (e.g. the LOGSE or the adaptation of the university studies to the European Space of Higher Education). As for the labour market, there are relevant differences in the probability of getting a permanent job between the different cohorts, due to the institutional design of the Spanish labour market. Young people exhibit much lower rates of stable jobs than older people, a feature that affects the decay of cognitive skills.

The presence of those cohort effects entails that we find differences in the groups even when we homogenize them by educational achievements or by age. As our model is mostly descriptive, the ensuing discussion is to be regarded as a guide to identify possible effects, to be later analysed in magnitude and relevance by more specific econometric studies (see Robles (2013) for an analysis of this type).

Differences by educational achievements: the impact of ageing

In agreement with the predictions of the generally accepted theory and the available evidence, the data from this study show a clear process of depreciation of cognitive skills due to the effect of ageing. Such a tendency is accentuated by the expansion of the years of schooling in the younger generations. This common pattern, though, is compatible with differentiated profiles by educational achievements.[9]

We have seen that the evaluation of youngest cohorts with compulsory and secondary education is well above the others, and that there is a substantial reduction between the first and second cohorts (with a slight correction in the third cohort in the case of secondary education, before dropping again in the fourth and fifth cohorts in both formative grades). The population with a university studies shows a different profile, with increasing values until the third cohort and a significant drop in the last.

In order to understand the sharp drop in the evaluation of the second cohort with respect to the first, for the population with secondary and compulsory studies (a 35% reduction in one case and 27% in the other), and the different behaviour of those with university studies (a 4% increase), we should take into account three aspects that work in a complementary way. Firstly, the number of years elapsed since the individuals quit studying up to the moment in which the surveys were carried out (worse results as more time elapsed). In the case of the population with compulsory education that had finished studying at the time of the survey this time span is a minimum of nine years (six in the case of secondary education), while in the case

[9] It is worth not mistaking this process of depreciation by cohorts described by our cross-sectional data with the intrinsic depreciation of a given generation over time. Although similar patterns are both in cross-section and longitudinal data, the cohort effects may entail substantial differences (see Desjardins & Warnke (2012) for a discussion).

of university education it can be one or two years.[10] Moreover, some 60% of the population with compulsory education and 65% of the population with secondary education from the first cohort, were actually still studying (something which tends to improve the results obtained by the younger generation with respect to the next because of keeping active the process of formal learning). Secondly, there is an effect induced by the labour market that can also help explaining the sharp drop of the evaluation between the first and the second cohorts. Unemployment rates are particularly high in the youngest cohort during the last years. This implies that, even though the situation is better for the second cohort, those individuals between 25 and 34 have already experienced long periods of unemployment (see Table 8.5), which entails a faster depreciation of human capital in those groups (the "use it or lose it" hypothesis of Mincer & Ofek (1982)). Finally, the data also suggest the presence of quality changes in the education of the different cohorts. The outcomes might be showing the so called "LOGSE effect", i.e. the negative impact of the changes introduced by that law, which would have had a larger incidence on the population with compulsory and secondary education (see Felgueroso et al (2013) and Robles (2013) for a discussion).

The negative impact of ageing does not show in those individuals with university studies until very late (the fourth cohort). We find also here several factors that may explain such behaviour. First, the fact that lot of people in the second cohort kept studying (50 % of the people in the first cohort with university degrees were continuing their studies). Second, the job market seems to enhance this extension of the learning process in a two-fold way. On the one hand, the unemployment rate goes down with age much faster for the population with university studies. On the other hand, because the quality of employment also increases very rapidly with age for those individuals (the share of temporary occupied over the occupied is halved from one cohort to the next). So, people with university studies end later their formal education and exhibit better employment conditions, which may delay the depreciation of cognitive skills.

Yet there may also be other variables that affect negatively the younger cohorts with university studies. One is that the extension of tertiary education may involve some trade-off between quantity and quality (especially bearing in mind the small fraction of 15-year old students in the higher levels of competence shown by the PISA surveys). There is also some evidence that the adjustment between education and employment may better for the intermediate cohorts than for the younger ones (negative effects of over-qualification on the preservation of abilities). Finally, we cannot exclude the presence of differences in the quality of university studies between the intermediate cohorts and the youngest and oldest cohorts.[11]

[10] This is assuming that they finish their studies in the corresponding year, which is not always the case. Indeed, many students are finishing their degrees around 25 years of age.

[11] One may also consider that the depreciation of knowledge in this population exhibits a greater durability. This is a subject under discussion about which the data do not yet give enough evidence (Desjardins & Warnke (2012, p. 47).

Table 8.5: Unemployment and temporary employment by cohorts and educational achievements (%)

Cohorts	Unemployment rate	Long run unemployment rate	Ratio temporary employed /employed
Compulsory education			
24 or less	59.69	30.12	50.39
25-34	38.34	18.88	30.85
35-44	31.36	16.26	23.17
45-54	28.52	16.34	16.43
55 or more	21.90	14.14	8.61
Secondary education			
24 or less	45.28	16.85	55.32
25-34	24.46	10.57	26.42
35-44	20.96	9.79	17.00
45-54	16.02	8.60	10.58
55 or more	14.62	9.79	5.58
University studies			
24 or less	37.78	9.71	75.23
25-34	17.51	7.17	32.03
35-44	10.43	5.00	14.02
45-54	7.36	3.62	6.49
55 or more	6.91	4.00	3.77

Source: INE, EPA Primer Trimestre 2012

It is worth mentioning that there is no evidence of relevant changes in the composition of the studies concerning the scientific or literary orientation (see Robles (2013)).

Differences by age: the impact of education

There is extensive evidence on the importance of formal education in cognitive skills (Statistics Canada & OECD (2000), (2005), Desjardins (2003), Ijzendoorn et al (2005)). Separate evaluation of the population by age allows us to estimate the relevance of non-compulsory with respect to compulsory education through the generations.

The data clearly show three relevant features in the cohort profiles. First, there is a lower relative value for university education in the youngest generation: 6.4 times the worth of compulsory education compared to between 9.2 and 13 times for the other cohorts, with a maximum for the fourth cohort (the same happens with university education relative to secondary education, as seen from the data in the footnote nº 8). Second, the worth of secondary education in the second cohort differs from the pattern of the rest of the cohorts, as it drops below that of the third. And third, the relative worth of university education with respect to compulsory education drops noticeably in the oldest generation with respect to the previous cohort (the same happens when we compare the worth of university studies relative to secondary education).

The elements that can explain those differences have already been mentioned. On the one hand, the outcomes of the population with compulsory or secondary studies aged 24 or less are not fully comparable with those of other cohorts. The reason is that such a cohort includes, among the population with compulsory or secondary education, many individuals who will end up with higher education (more than half of the youngest generation kept studying when the test was carried out). They are endowed, therefore, with abilities that go beyond the average educational achievement they have reached at the time of the survey. On the other hand, the quality of the university studies of the youngest may be less than that of older cohorts as a result of the late changes in the university system (the particular way of implementing the adaptation of the Spanish university system to the European Space of Higher Education).[12]

The generation between 25 and 35 years old is the one that has experienced the educational change associated with the LOGSE, which started to be implemented from 1991 until completion in 2002. The results of individuals in this cohort with compulsory and secondary education may be reflecting the adjustment costs of the reform. This effect is not clear for those with university studies.

Finally, the relative worth of university studies drops noticeably in the last generation, contrary to what happens with secondary education. Thus we note that the greater relevance of having university studies in that cohort does not offset the depreciation of knowledge due to ageing (even though the worth of the university studies for this last cohort would still be above that of the third). It is possible that the quality of university studies of that generation is below the previous ones and also that the share of people early retired may be significant, which would induce a sharper decline of cognitive skills.[13]

An overall evaluation of the cohorts

The above results are based on the analysis of the distribution according to competence levels of the population of each cohort and formative stage. Let us consider now the educational structure of the different cohorts. That is, the distribution of educational achievement within each cohort (see Table 8.6).

Table 8.6: Distribution of the educational achievements by cohorts (%)

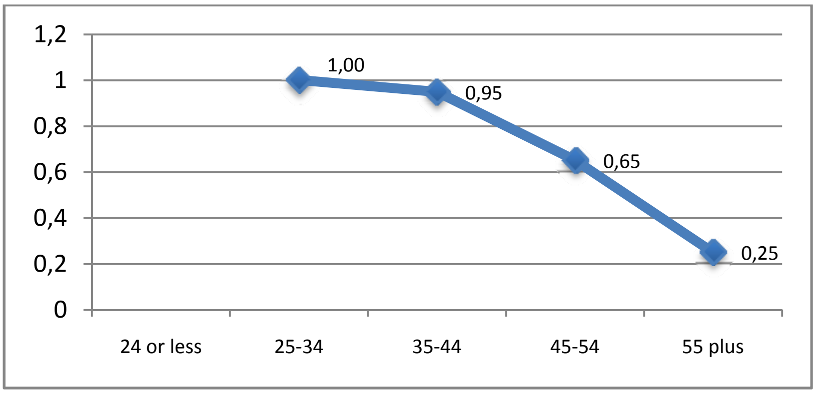
	Studies		
Cohorts	**Compulsory**	**Intermediate**	**University**
24 or less	52.03	41.10	6.87
25-34	34.07	36.87	29.06
35-44	39.54	33.36	27.10
45-54	49.81	28.58	21.62
55 or more	63.96	22.66	13.38

[12] Note that the population of less than 24 years old that has achieved a university degree is very close to having finished their studies in the time theoretically required (so that there will be a significant fraction of the best university students of their generation in this cohort). Furthermore, we also find in this case that half of the young people with university studies were still studying when the tests were performed, which would also be redundant in a higher valuation.
[13] This is an aspect that requires further analysis, as it is not easy to identify what is behind the smaller worth of university studies in the older generation.

The data show the extension of non-compulsory education in Spain during the last decades (66 % in the second cohort versus 36 % in the oldest one).[14] We can combine these data with those in Table 8.3 (A) in order to get an ***overall evaluation of the cohorts***. To do this we attach to each cohort a value that corresponds to the weighted average of the worth of the different educational achievements, using as weights the corresponding fraction of the population.

The results of this exercise are described below (Graph 8.4) taking the value of the second cohort equal to one and leaving the first cohort out of the comparison, for the reasons stated in footnote nº 14.

Graph 8.4.- Overall evaluation of the cohorts



The graphic shows a profile that clearly decreases with age. The worth of the fourth generation is around 70% of that of the third and the value of the fifth does not reach 40% of that of the fourth. The sharp drop in the valuation of the fourth and fifth cohorts is derived from the combination of the lower value of the older cohorts for each formative stage, with the smaller proportion of population with higher education in these cohorts.

CONCLUSIONS

In this study we have carried out an evaluation of the cognitive skills of the different generations, using the information on the distributions of each group in the five competence levels defined in PIAAC. The evaluation of each group is associated with the probability that a randomly chosen member of a group be in a higher level of competence than any other individual randomly chosen from the other groups. It is interesting to highlight that our evaluation discriminates much more between groups than the average scores of the test does.

[14] The distribution of educational achievements of the youngest generation deserves a separate comment in the light of the values of the population with university studies and compulsory education. The low proportion of the population with university studies is explained by the fact that only a small fraction of those individuals between 16 and 24 years old may have completed their university studies, due to age. Moreover, more than half of the individuals in this cohort are still studying (60% among those with compulsory education, 65% of those with intermediate education and 50% of those with university education). Consequently, the graphs on the distribution of educational achievements in this cohort may be very misleading.

The results obtained clearly indicate that formal education is the basic determinant of the relative value of human capital of the different cohorts. This conclusion is in line with the results of other studies, in particular the analysis of Desjardins (2003) on reading literacy in adults: education turns out to be the key variable in explaining this competence, over and above the role played by the family environment or experience in the workplace.

The depreciation of cognitive skills due to ageing is another of the relevant aspects of the results obtained, with noticeable differences both in terms of levels as well as rates of variation for the different educational achievements. This depreciation results in a reduction in proportions of population in the higher competence levels and an increase of the population at the lower levels. One of the variables that seems highly related to the depreciation of cognitive skills is the number of years elapsed since finishing formal studies until the realization of the PIAAC test. This would reflect the delay effect in depreciation due to the accumulation of so-called *crystallized cognitive skills*.

The employment status is another element that appears as playing a role in the depreciation of cognitive skills. Unemployment and job instability not only affect the income and welfare of families but they also undermine human capital, so that part of the investment in education is rapidly lost due to these circumstances.

Our evaluation also points out that the changes in educational structure may have relevant implications for the future performance of the generations that experience them. Both the introduction of the LOGSE and the particular adaptation to the European Space of Higher Education carried out in our country seem to have had some negative implications on the cognitive skills of the generations that have suffered the change.

Finally, let us mention that the outcomes of our study suggest that we should be cautious when interpreting the message that today's young people are the ever best educated generation. While Graph 8.4 seems to support that conclusion, it must be remembered that the higher overall worth of young people from 25 to 34 years old has much more to do with the percentage of population with higher education than with the differential value of their cognitive skills when compared to their peers. The separate evaluations by educational achievements and by age show just this.

From this analysis it follows that continued learning processes and adequate integration into the labour market are the key tools for maintaining human capital investments, due to its effect in delaying the depreciation associated with ageing. Let us recall here that the good results of the first cohort with respect to the second, for secondary and compulsory education, are partly related to the fact that many of these individuals were still studying. And also that individuals with university studies exhibit a slower pattern of decay. The current high levels of unemployment, mostly among the young (with the associated deterioration of the cognitive skills achieved), the process of progressive ageing of the population, the fast technological changes, and the delay of the retirement age, mean that finding effective ways to update and improve education is especially relevant. In the words of the OECD's General Secretary: "The most promising solution to these challenges is to invest effectively in the development of skills throughout the life cycle; from earliest childhood, through compulsory education, and throughout the whole working life "(OECD (2012, p.3)).

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Conclusions

CONCLUSIONS

The OECD Programme for the International Assessment of Adult Competencies, PIAAC, and the research included in this publication provide valuable information to analyse various economic aspects. The ultimate objective of this book is to shed light on the subject to improve adult education and lifelong development of competencies. In Spain, this is a particularly relevant topic for analysis, as the adult results in our country are significantly lower, both in literacy and numeracy, than in the rest of the participating countries (except Italy) and the average of the OECD and EU participating countries, with the impact this has in terms of productivity and ability for innovation in the workplace, as well as its effect on other variables in the private and social areas.

It is only fair to highlight the importance of the reflections and analyses in this paper given the depth and quality of the empirical studies in this publication, which have been conducted by leading-edge, renowned researchers, who are affiliated with prestigious universities and institutions and are known for their dedication to excellence.

Based on the information presented by the various empirical studies included here, we can identify a series of features, such as the role of the education system, the depreciation of human capital with age, the importance of initial and continuing education and the influence of work experience, among others.

EDUCATION LEVEL, OCCUPATION AND SKILLS AND COMPETENCIES

The PIAAC results by education levels show there is a clear positive association between the maximum education level attained by an individual and the results achieved in literacy and numeracy.

The average scores in literacy and numeracy of working Spaniards are medium-low (the average is at level 2). Among university students, over 50% are at level 3 or higher (over 275 points). At the opposite end are individuals with primary education, where 50% do not exceed level 1 (225 points).

The professors of the University of Valencia, members of the Institute of Economic Research of Valencia (IVIE), Francisco Pérez García and Laura Hernández Lahiguera, describe the level of competence of working individuals. In their analysis, they show the huge contrast that exists between the lower level of competencies of business owners and the higher level of public employees and managers. These differences can be explained by the academic education of the various categories of workers, where the majority of public employees (64.8%) and managers (54.5%) are graduates (university degrees and advanced vocational education and training). In contrast, only 34% of business owners attain this level of education.

Professor Julio Carabaña, of the Complutense University of Madrid, based on PIAAC data, determines that the years of schooling in primary education are especially important for literacy proficiency and they have a much greater impact on results than the years of schooling in post-compulsory education. This author states that literacy scores improve with age and experience, but schooling has no effect after age 16.

TRAINING, WORK ENVIRONMENT AND COMPETENCIES

The Professors of the Department of Economics of Carlos III University, Antonio Cabrales, Juan J. Dolado and Ricardo Mora warn that Spanish temporary workers receive less training from companies than those with permanent contracts, which implies lower competencies for the former. Corporations have few incentives to invest in developing their temporary workers, while in turn these workers do not have the necessary incentives either to enhance their performance by improving their productive capacities.

Cabrales, Dolado and Mora point out the negative relationship between work precariousness and training in corporations and they discern a positive relationship between training activities and the cognitive abilities of workers. They state that: “To the extent that an improvement in the educational levels of the Spanish population is a *sine qua non* condition for improving welfare through increased competitiveness in technologically-advanced sectors, reducing the excessive segmentation of the Spanish labour market seems to be an essential policy measure”.

Juan Francisco Jimeno, Aitor Lacuesta and Ernesto Villanueva, from the Research Division of the Bank of Spain, suggest that: “Labour market experience is associated with an increase in cognitive skills, especially with respect to the numeracy test results, at the beginning of the working life, especially among the younger cohorts, and in the case of workers with low educational levels”.

Jimeno, Lacuesta and Villanueva determine that work experience is associated to an increase in salary that is higher for workers who have attained university education than for those with a low level of education, as well as that the type of tasks conducted on the job and the rate of continuance on the job help explain these differences. Among individuals with elementary education, those conducting mathematical tasks in their job attain approximately 10 points more in the math tests, compared to those who do not. For individuals who have completed university studies, the impact of advanced tasks reaches 20 points.

The authors highlight one important element: "The fact that specific tasks contribute to increasing cognitive skills and others not, should shape the direction of job training. Secondly, the fact that job stability is important in encouraging learning on the job, especially among workers with higher educational levels, is one more element to take into account when addressing the problem of excessive job turnover that characterizes the Spanish labour market".

Pérez García and Hernández Lahiguera (IVIE), confirm the existence of productive environments (industries, companies), more favourable for human capital and the existence of higher competency levels among those working there. There are five industries where the average scores exceed 275 points and are on level 3 of the scale: ICT; financial and insurance services; scientific, professional and technical activities; education, and extractive industries. As for the role of the size of corporations, the highest competency levels of workers in larger companies are due to their higher levels of education (their human resources recruitment criteria result in a higher proportion of workers with a higher level of education).

Antonio Villar, professor at the Pablo de Olavide University, determines that lifelong learning processes and adequate integration in the labour market can be useful to maintain the stock of human capital as they delay the depreciation associated to ageing. The population with a university education has a far less marked depreciation profile than the rest, starting much later. This reflects the effect of delayed depreciation due to the accumulation of the so-called "crystallized cognitive abilities".

Villar points out that: "The current high levels of unemployment, mostly among the young (with the associated deterioration of the cognitive skills achieved), the process of progressive ageing of the population, the fast technological changes, and the delay of the retirement age, mean that finding effective ways to update and improve education is especially relevant".

Professor José Antonio Robles, from Pablo de Olavide University, infers that cognitive abilities seem to develop in a more lasting manner among those individuals who are working and those using numeracy and literacy at work or at home. Therefore, life experiences affect the rate of depreciation of human capital. Nonetheless, the eventual depreciation of human capital among the older groups seems a general phenomenon that takes place regardless of an individual's life experiences. In the data analysis, the author detects a negative trend after implementation of the LOGSE *[General Organic Law of the Educational System]* for math proficiency, not affecting literacy.

IMPORTANCE OF QUALITY IN THE EDUCATION SYSTEM AND ITS RELATIONSHIP WITH WORK

The professors of the University of Valencia, members of the Institute of Economic Research of Valencia (IVIE), Laura Hernández Lahiguera and Lorenzo Serrano Martínez, underline that: "A mere quantitative increase of the educational system and its expansion including larger parts of population, will produce less satisfactory results for students and the whole of society unless it is accompanied by a determined effort to improve quality.". Policies fostering better functioning of the education system, with better results in terms of the knowledge and competencies attained by the students, can have noticeable positive effects on the rates of employment and unemployment, as well as on productivity on the job and, in short, on income per capita and the standard of living of the population.

Hernández and Serrano indicate there is a clear correlation between the salary level declared by participants and the results achieved in literacy and numeracy, especially among the highest salary levels. Knowledge is a very relevant determinant for job performance, and for salaries, especially math competencies, which appear to be the most decisive in driving worker productivity.

The Professor of La Laguna University, José Saturnino Martínez, studies the case of over-qualification, especially among university graduates, pointing out that unequal opportunities are derived from the relationship between social background and educational performance, not so much from the relationship between social background and the labour market (the labour market discriminates by level of education, not by social background). This author indicates that improving equal opportunities through education policies rather than work policies would produce a greater effect.

SUMMARY

In short, reading and disseminating these studies can support decision-making for education and employment policies. Reading these studies helps emphasise the importance of lifelong training for human capital as they rigorously present its impact on the key variables for a country's development, such as productivity, technological capacity, innovation and development, competitiveness and financial growth.

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