Persons

Income returns to complex problem solving skills are strongly significant

POLICY BRIEF
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Productivity of skills

Persons

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Persons

INCOME RETURNS TO COMPLEX PROBLEM SOLVING SKILLS ARE STRONGLY SIGNIFICANT

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Introduction

Why do we invest in our skills?

One of the basic facts of economic life is that different people earn vastly different salaries. Economists have traditionally attributed differences in earnings to differences in human capital and skills (e.g. Roy 1951). Individuals that have a higher level of skills are more productive and hence receive larger compensation in the competitive markets, keeping other things constant. But what specifically is human capital? Gary Becker (1993) defined by human capital all factors embodied in a human being, investments in which increase individual productivity. This sounds like a broad term, and indeed it is. Education, health, abilities, skills, work habits and knowledge are all examples of some forms of human capital.

Due to generality of human capital it is difficult to measure it precisely and assess independent contribution of its different forms to productivity and wages. Because of that economic research mostly focused on investigating the contribution of factors that are relatively easy to observe, such as education and work experience. However, it is implausible that just these two measures are sufficient to represent the amount of human capital embodied in every person. More refined measures are necessary in order to understand the functioning of labour markets and to draw policy implications. Thanks to the data collected in the LLLight'in'Europe project there is a first time opportunity to investigate the economic significance of complex problem solving (CPS) skills using MicroDYN and MicroFIN computer-based test environments.

This policy brief discusses the role of human capital and more specifically CPS skills in determining wages. CPS skills are found to contribute significantly to earnings and their importance for success on the labour market is likely to remain high due to prevailing structure of the demand for skills.

Key observations

Different types of human capital contribute to earnings unequally

Education, work experience, on-the-job training, abilities and talents, family background are all important determinants of labour market outcomes such as earnings and employability, but they play unequal roles. To assess the relative importance of different factors, we employ regression analysis which allows to decompose the variation of wages according to each contributing factor. The standard approach to analyse earnings' determinants is the Mincer regression (Mincer 1974), which models the logarithm of earnings as a function of education and years of work experience.

Most estimates of the economic returns to schooling published in the past suggest that each additional year of schooling raises earnings by a constant factor of 5–8.5% or 6–15% when estimated using the instrumental variables technique (Card 1999). In comparison, the marginal effect of each additional year of work experience is smaller and is varying with years worked (fig. 1). In any given population the contribution of the factors to variation in earnings will depend both on the extent of variation in the factors and on their marginal effect on the outcome.

Figure 1: Marginal returns to a year of schooling and work experience.

Notes: panel a): marginal return to one year of schooling (dashed line) and to one year of work experience (solid line). Panel b) reports the same quantities once the variation in literacy skills is taken into account. The marginal return to work experience is largely unaffected, while the return to years of schooling is decreased from 6.2% to 5.2%.

Data source: estimated using the PIAAC data.

To what extent do the basic measures of human capital capture the variation in wages? An analysis performed with Eurostat Structure of Earnings Survey suggests that only 23% of variation in the logarithm of wages is attributable to the strength of the effect and the extent of variability of education and age (see table 1).

The share of variation attributable to education is about 55% larger than to age. Given that, education appears to be quantitatively more important than the accumulation of job related human capital over lifetime. However, the importance of education may be overestimated whenever the estimation procedure does not correct for the influence of unobservable skills (Blau and Kahn 2005). Without accounting for skills it is impossible to draw conclusive policy implications, because we cannot tell whether it is education that contributes to the variation in earnings or unmeasured skills that are masked by education.

Table 1: Decomposition of the share of explained variance in the Mincer regression

Variable	Age	Education	Gender	Full time	Year	Region
Share of variance	0.09	0.14	0.02	0.00	0.00	0.22

Notes: R^2 of regression is 47%. Countries included: Belgium, Greece, France, the Netherlands, Portugal, Spain and the United Kingdom. Data source: estimated with the Mincer regression using OLS on a sample of EU countries from the Eurostat SES data for 2006 and 2010. The decomposition was performed with the ANOVA-III test.

In order to incorporate skills into the decomposition of wages, one needs to precisely define and measure skills. One such analysis is due to Cawley, Heckman, and Vytlacil (2001), who construct a measure of cognitive skills from the ASVAB intelligence tests in the US National Longitudinal Youth Survey data and find that a change in intelligence test score from the 25th to 75th percentile is associated with an increase in wages by 10–15% depending on race and gender. The PIAAC study provides international evidence on broad cognitive skills such as literacy and numeracy across OECD countries. Hanushek et al. (2015) estimate the returns to skills measured in the PIAAC survey. In their comparable specification one standard deviation of numeracy skills yields 10% higher earnings. These analyses are limited to estimating the impact of a specific type of measured skills.

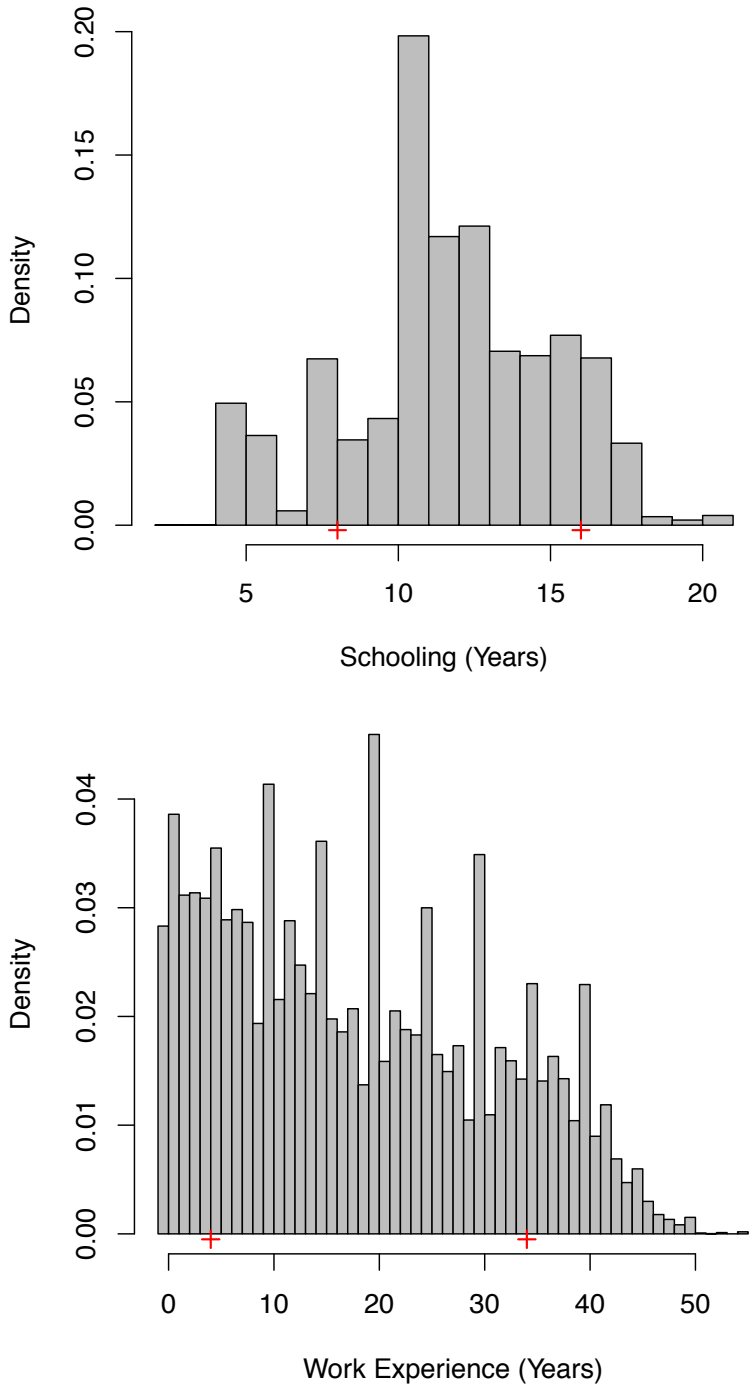
Heckman, Stixrud, and Urzua (2006) model choices of the level of schooling, type of employment, work experience and engagement in risky behaviour using measures of both cognitive and noncognitive skills. Cognitive skills are again calculated from the ASVAB test, while noncognitive skills are measured using Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale. They find that both cognitive and non-cognitive skills affect labour market outcomes and schooling choices, and the effect of non-cognitive skills is at least as large as that of cognitive skills.

Complex problem solving skills contribute to wages

Ederer et al. (forthcoming), using the data collected in the period 2012–2014 from employees in Denmark, Germany, France, Slovakia, South Africa, Spain, and Switzerland, estimate that an individual at the 15th percentile of the CPS skill distribution earns 20% less compared to an individual at the 85th percentile. (This estimate takes into account differences in education, years of work experience and managerial responsibility.) Such difference in earnings is in the range of the estimates of the returns to literacy, numeracy and problem-solving skills by Hanushek et al. (2015) and to cognitive skill in Cawley, Heckman, and Vytlacil (2001). Given the magnitude, the CPS skill is an important determinant of earnings.

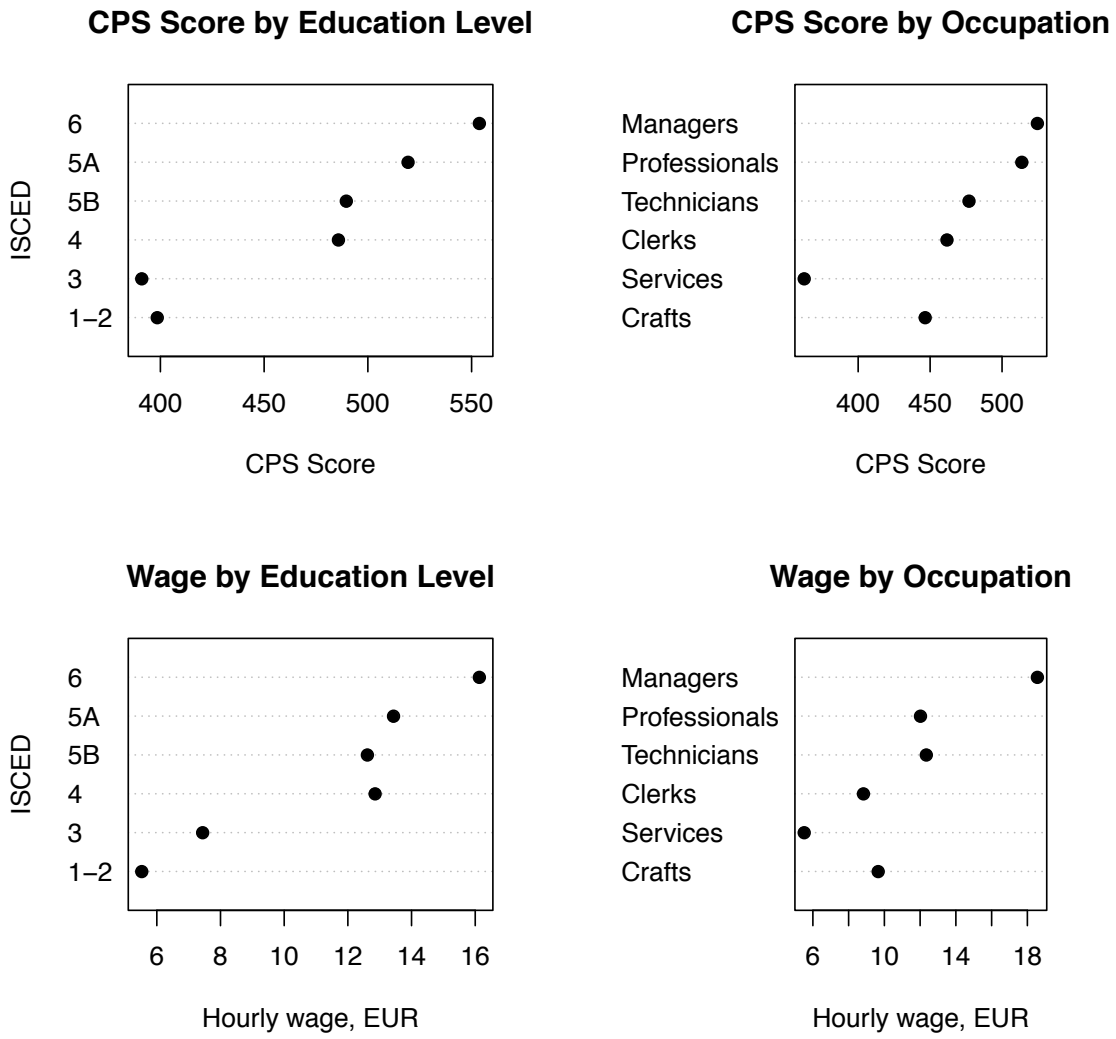
How do the returns to CPS skills compare to returns to other human capital measures? In the PIAAC data set the difference in years of schooling between the 15th and the 85th percentiles of the distribution of schooling across all participating countries corresponds to 6 years (see fig. 2). If we take 6% as an estimate of the return to a year of schooling, this translates into 36% earnings difference. As for work experience, the corresponding difference is between 4 and 34 years, which translates into 41% earnings difference. Therefore, the magnitude of the variation in earnings attributable to CPS skills makes them comparable in importance to other measures of human capital. Needless to say, individuals who excel in the CPS test are also much more likely to have a high level of education and be employed in an occupation that pays well (fig. 3).

Figure 2: Distribution of years of schooling and work experience in a sample of EU countries.



Notes: the height of every bar corresponds to the proportion of individuals in the sample who have corresponding years of schooling or respectively work experience. The position of the 15th and 85th percentiles is indicated by crosses. Data source: PIAAC. The sample consists of participants from Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Ireland, Italy, the Netherlands, Norway, Poland, Slovak Republic, Spain, Sweden and the United Kingdom. Austria, Canada, Germany and USA are excluded, because these countries do not provide data either on work experience or years of schooling. Japan, Korea and Russia are also excluded in order to make the sample more comparable to EU countries.

Figure 3: Complex problem solving skills and wages by education and occupation.



Notes: CPS scale is constructed such that 500 points is the sample average and 100 points is one standard deviation. Education is measured according to ISCED 1997 UNESCO classification.

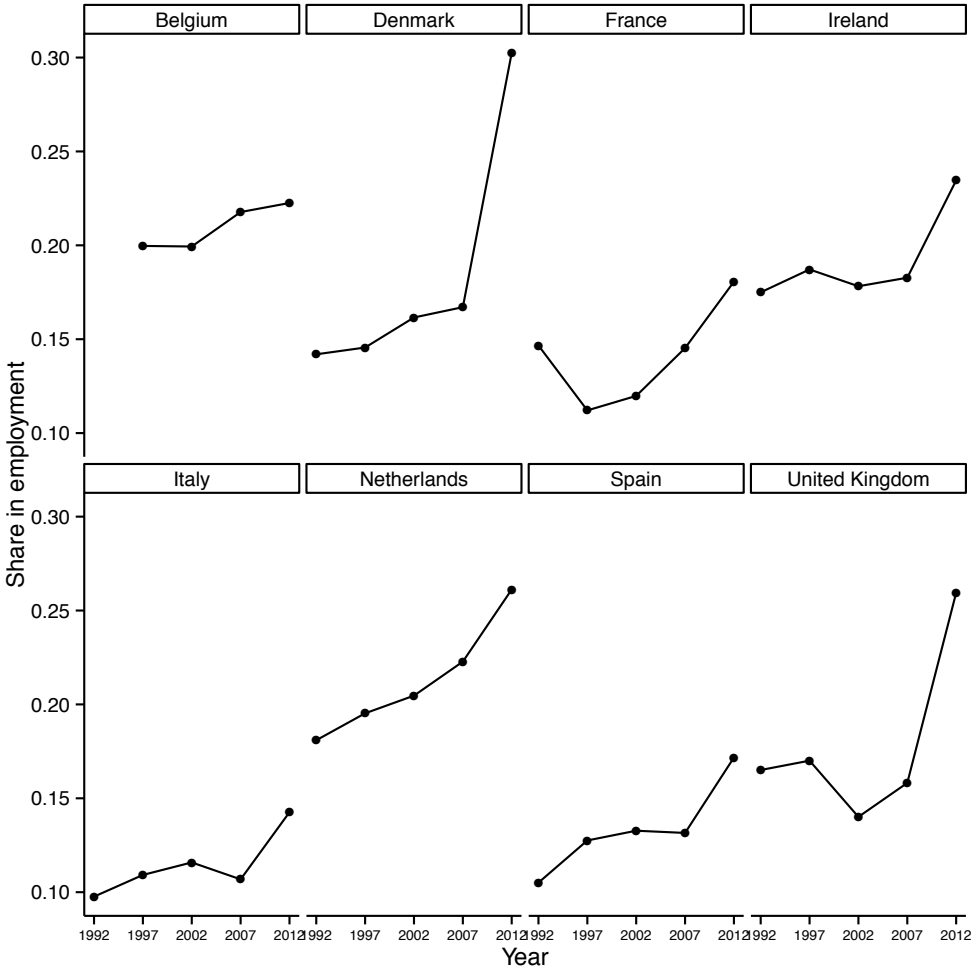
Data source: LLLight'in'Europe.

Rising cognitive complexity of jobs is likely to increase the returns to complex problem solving skills

The importance of complex problem solving skills is highlighted by the fact that the share of employment in managerial and professional occupations has increased considerably in many European countries in the past 20 years (see fig. 4). Individuals employed in these occupations have high measured CPS skills that are statistically different from other occupations, in particular from service and crafts workers (see fig. 3), whose scores are more than one and a half standard deviations below. Such a large difference suggests that CPS skills may be intensively used in highly skilled occupations and are a precondition in order to get such jobs.

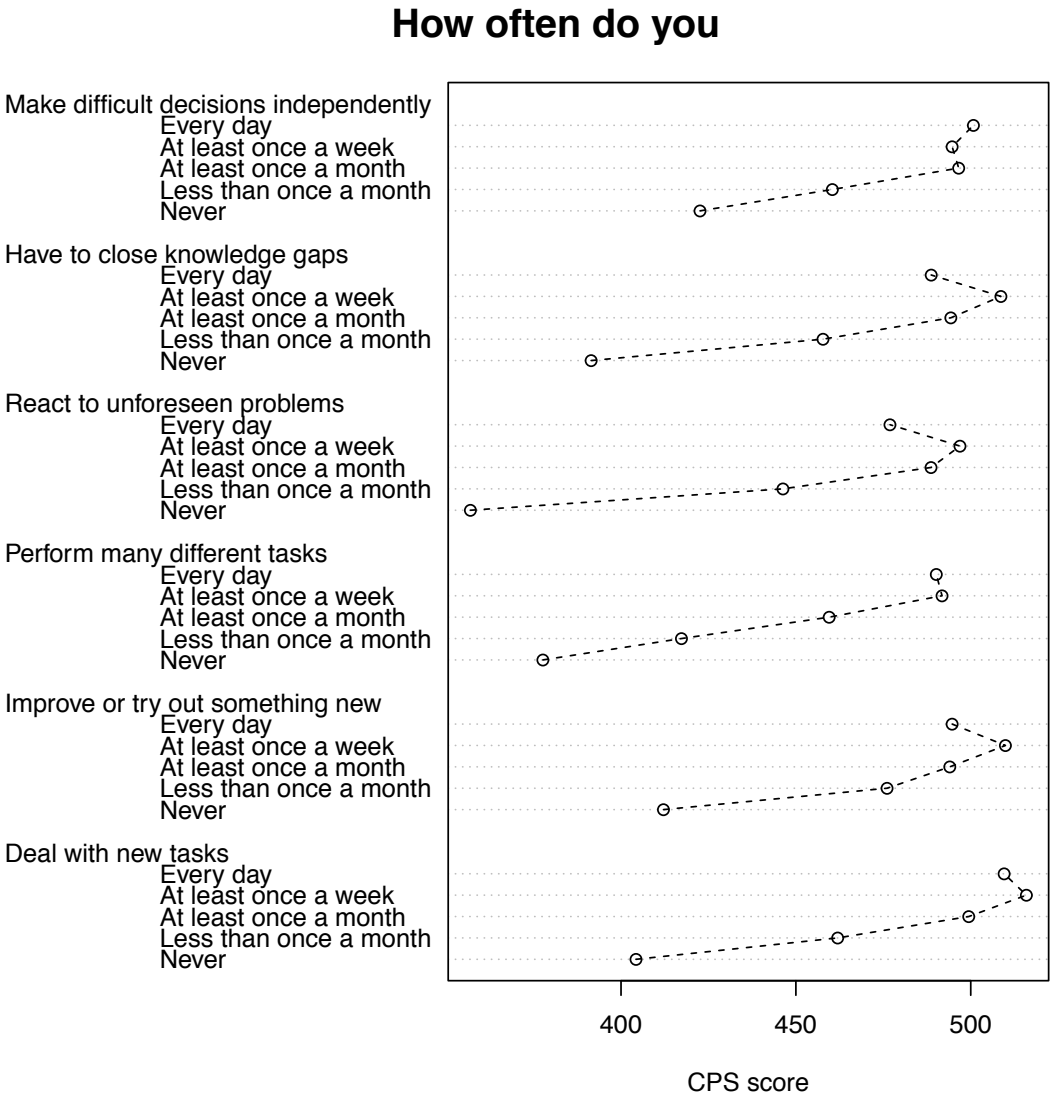
There are no presently available historic data on CPS skills of working adults to draw comparisons with the past. Based on the fact that CPS skills are strongly correlated with engaging in tasks at work that are intensive in problem solving, acquiring knowledge, dealing with novelty and complexity (fig. 5), it is nevertheless possible to use the data on task utilisation across the occupational spectrum to construct a proxy measure for problem solving (analytical) skills on the occupational level. Such calculations assume that there is no substantial discrepancy between job requirements and skills that employees actually have, while allowing a more accurate reconstruction of historical trends. Using US IPUMS data set, we find that market returns to problem solving skills have remarkably risen over the past quarter century (see table 2). In 1990, a percentile difference in the job complexity measure constructed using problem solving task data yielded 0.44% difference in earnings. By 2010 the difference had increased to 0.72%, i.e. by as much as 64%. For the same time period the returns to education remained stable. These findings suggest that the demand for complex solving skills has been on a rise and such skills have become increasingly more important for work.

Figure 4: Share of managers and professionals in total employment.



Data source: constructed using Eurostat LFS data.

Figure 5: The relation between CPS scores and work tasks.



Notes: CPS scale is constructed such that 500 points is the sample average and 100 points is one standard deviation.

Data source: LLLight'in'Europe.

CPS can explain some income inequality across gender

Males benefit from CPS skills equally with females, even though in the data males have higher CPS scores by 60 points (about 2/3 of one standard deviation), keeping age constant. Because of that the CPS skill can explain part of the earnings gap between males and females. The difference in wages between males and females is reduced from 18.5% to 13.3% in the data once the variation in the CPS skill is taken into account in addition to other determinants of wages.

Which factors contribute to gender difference in CPS skills? In the collected data males and females have similar participation rates in tertiary education, while relatively more males completed vocational degrees and more females have only upper and lower secondary education. Males are considerably more likely to be employed as managers and less likely as service workers or clerks. Taking into account differences in education and employment across males and females, the gender difference in the CPS scores is reduced from 60 points to 44 points. In addition to that, personality traits also play a role, as males on average scored higher on the conscientiousness dimension of the Big 5 model (Costa and McCrae 1992), which helps to reduce the gender gap in the scores down to 36 points.

Policy recommendations

As investment in education is mostly incurred at the beginning of one's adult life, improvement of CPS skills may provide a way to increase earnings potential at the later stage of career, especially when switching to a highly skilled occupation such as managers or professionals that requires such skills. Historically rising demand for work complexity suggests that income inequality will widen, as individuals with high levels of CPS skills will earn even more. Therefore, it is important to understand what forms investment in CPS skills can take.

Existing evidence on the development of CPS skills is scarce. Cunha and J. Heckman 2007 summarise evidence on the development of cognitive ability and conclude that balanced investment in early and late childhood is most rewarding.

They also stress the economic and social importance of noncognitive skills. We find that CPS skills are correlated with the level of education, intelligence, socio-demographic characteristics, personality traits and learning attitudes. While most of these factors are not easily changeable, improving the learning attitudes towards open-mindedness and learning new things may allow one to benefit more from problem solving incidents. The relation between CPS skills and problem solving tasks at work suggests that choosing complex jobs which provide a favourable environment for learning and problem solving may be one venue to improve one's CPS skills.

Evidence and background

We use the standard Mincer earnings function framework to estimate the economic effect of CPS skills (see Mincer 1974; Griliches 1977; Willis 1986). The Mincer equation summarises the relation between earnings and human capital measures for individual i:

$$\text{Log Wage}_i = \alpha + \beta_1 \text{WorkExp}_i + \beta_2 \text{WorkExp}^2_i + \gamma \text{School}_i + u_i, \quad (1)$$

where α, β and γ are constant coefficients, WorkExp is years of work experience, and School is a measure of education (typically, in years). u_i is the residual. This model reflects two central facts about earnings:

1. Earnings grow with years of work experience at a decreasing rate (whenever $\beta_2 < 0$);

2. Earnings profiles are parallel for varying levels of education.

An equation like (1) naturally arises as a special case of a model with linear preferences and a linear relation between the percentage of change in productivity and schooling (see Card 1999). The literature traditionally derived the log linear relation above in the context of investment in training (Ben-Porath 1967; Willis 1986).

It is no doubt that a simplified specification like (1) misses many important features of the real world. Neither education, nor work experience, nor skills can be measured perfectly and without any error. The variable representing the level of education does not reflect differences in the quality and content of education across countries, regions, schools and teachers. Tenure is difficult to measure precisely. Some individuals work while studying and some have multiple jobs. If tenure is used as a crude measure of the growth of work related experience and knowledge, then it cannot succinctly capture the differences in the scope of such learning across jobs (see Nedelkoska, Patt, and Ederer 2014 and Yamaguchi 2012). However, available evidence suggests that the measurement error problem in years of schooling is not as severe as one may think and leads to understatement of the coefficient of education by about 10% (Card 1999). The other source of concern in estimating the Mincer model is the omitted variable bias, for example due to absence of ability or family background variables. Highly able individuals are likely to choose higher levels of schooling and at the same time be more successful and productive workers. A number of studies used exogenous variation in schooling determinants in the framework of IV regression and concluded that OLS estimates of the returns to schooling underestimate true returns. Card (1999) provides a useful summary of this research.

Following studies such as Griliches (1977) and Cawley, Heckman, and Vytlacil (2001), we treat CPS skills as an omitted variable in the baseline Mincer model that enters the relation linearly and separately. The results of the estimation are presented in table 3. While the estimation of the coefficient of the CPS skills may also be prone to the same issues as with estimating the effect of education, estimations that control for family background and personality yield nearly identical results.

Table 2: Historical rates of return to education and job complexity.

Year	*1990*	*2000*	*2005*	*2010*
Job complexity	0.44	0.55	0.64	0.72
Schooling	*7*	*7*	*8*	*7*

Notes: job complexity is measured in percentiles. Schooling is measured in years. Thus in 1990 one year of schooling increases earnings by 7%, while one percentile difference in the job complexity index by 0.44%.

*Data source: estimated using IPUMS data. Job complexity measure is derived from the O*NET data.*

Table 3: Regression results of the earnings equation with CPS skills.

	Model 1	Model 2	Model 3
(Intercept)	0.500 (0.099) ***	1.715 (0.078) ***	0.637 (0.102) ***
ISCED 3	0.497 (0.086) ***		0.477 (0.084) ***
ISCED 4	0.557 (0.080) ***		0.494 (0.080) ***
ISCED 5B	0.671 (0.077) ***		0.595 (0.078) ***
ISCED 5A	0.908 (0.068) ***		0.794 (0.072) ***
ISCED 6	0.963 (0.100) ***		0.831 (0.103) ***
Male	0.196 (0.039) ***	0.177 (0.048) ***	0.138 (0.040) ***
WorkExp	0.045 (0.007) ***		0.049 (0.007) ***
WorkExp2	-0.001 (0.000) ***		-0.001 (0.000) ***
CPS		0.167 (0.024) ***	0.108 (0.024) ***
R^2	0,668	0,528	0,681
Adj. R^2	0,655	0,516	0,668
Num. obs.	494	494	494
df	475	481	474
Mean dep. var.	2,296	2,296	2,296
BIC	550	686	537
S.E.R.	0,38	0,45	0,373

*Notes: Model I is the result of estimating the standard Mincer model with OLS. The dependent variable is hourly wage rate in Euro. CPS is measured in standard deviations. Model II is a regression of wages on the CPS skill and controls. Model III is the Mincer model which includes the CPS skill. All models control for country. Significance levels: *** p < 0.001, ** p < 0.01, * p < 0.05. The estimation results replicate Ederer et. al. (forthcoming) on a larger sample.*

Data source: LLLight'in'Europe.

Analysing the decomposition of earnings variation in detail

When used as a single measure of human capital, the CPS skill alone contributes 8% of explanatory power to the regression of logarithm of wages on a set of controls. When education and work experience are added to the model, the marginal contribution of the CPS skill is reduced to 2%. In (Cawley, Heckman, and Vytlacil 2001) the marginal addition to R^2 of the earnings regression of a cognitive skill measure is also about 1–3%. This means that there is strong overlap between cognitive skills and other measures of human capital. CPS, education and the kind of employment that a person has appear to be tightly related.

The inclusion of the CPS variable into the standard Mincer regression of earnings does not affect the estimate of the marginal return to school education, but decreases the return to graduate education from 90% to 80% for bachelor and master degrees and from 96% to 84% for a PhD. As a result, the share of variation in earnings attributed to education falls by 26%, while the marginal contribution of work experience increases by 60% (see the table below). While education appears to be almost four times more important than work experience in predicting earnings in this sample, once the contribution of CPS skills is taken into consideration the relative importance of education is considerably reduced. Among education, work experience and CPS skills, the latter account for 1/12 of the contribution to explained variation in earnings.

Table 4: Decomposition of the share of explained sum of squares.

Variable	*I*	*II*	*III*
Country	0.43	0.44	0.45
CPS		0.08	0.02
Gender	0.02	0.02	0.01
Education	0.19		0.14
Work experience	0.05		0.08
R^2	0.69	0.54	0.70

Notes: the numbers indicate the shares of variance attributed to variables. Column I is the standard Mincer model. Column II is a model with CPS and controls. Column III is the Mincer model augmented with CPS. Refer to evidence and background section for details regarding the sample.

Data source: LLLight'in'Europe.

Details on CPS data collection and composition

The data used for investigations with CPS skills were collected in the period 2012–2015 from employees, self-employed and trainees of 40 companies and establishments in Argentina, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Slovakia, South Africa, Spain, Switzerland, United Kingdom and Uruguay. The share of participants from Germany is 44%, from Spain 16% and from Italy 8%. The employees come from companies operating in industrial, agricultural, services and information technology sectors.

The average number of participants per company is 24. Data collection was carried out at the companies' facilities and comprised of a CPS test, a background questionnaire and in some cases a general intelligence test, which were administered in the language spoken at the company or its branch. The participation was voluntary and anonymous. The average age of participants is 36 years and the average work experience is 14 years. 36% are females. 15% completed lower secondary education or less, 11% upper secondary education and 62% tertiary education. The largest employment groups are professionals (34%), managers (10%) and technicians (10%). The sample is therefore biased toward highly skilled individuals.

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Project Identity

LLLight'in'Europe is an FP7 research project supported by the European Union, which has investigated the relevance and impact of lifelong learning and 21st century skills on innovation, productivity and employability. Against the background of increasingly complex tasks and jobs, understanding which skills impact individuals and organizations, and how such skills can be supported, has important policy implications. LLLight'in'Europe pioneered the use of an instrument to test complex problem solving skills of adults in their work environment. This allowed for the first time insights into the development of professional and learning paths of employed individuals and entrepreneurs and the role that problem solving skills play. Additionally, LLLight'in'Europe draws on a series of databases on adult competences from across the world to conduct rich analyses of skills and their impact.

These analyses were conducted in concert with different disciplines. Economists have been analyzing the impact of cognitive skills on wages and growth; sociologists have been investigating how public policies can support the development of such skills and lifelong learning; innovation researchers have been tracking the relationships between problem solving skills, lifelong learning and entrepreneurship at the organizational level;. educational scientists have investigated how successful enterprises support their workforce's competences; cognitive psychologists have researched on the development and implications of cognitive skills relevant for modern occupations and tasks; and an analysis from the perspective of business ethics has clarified the role and scope of employers' responsibility in fostering skills acquisition in their workforce. The team has carried out its research and analyses on the value of skills and lifelong learning in EU countries, USA, China, Latin America and Africa.

The result is a multi-disciplinary analysis of the process of adult learning and problem solving in its different nuances, and of the levers which can support the development of these skills for both those who are already in jobs, and for those who are (re)entering the labor market, as well as the development of effective HR strategies and public policy schemes to support them.

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Persons

This policy brief is part of the publication suite of the FP7 Project LLLight'in'Europe. The publication suite consists of 21 policy briefs, 6 thematic reports and 1 synthesis report. The 21 policy briefs discuss findings and policy implications proceeding from the project's research; they are organized along three level of analyses (persons; enterprise; country) and seven topics.

01 Resources of society for learning

02 Institutions of learning

03 Circumstances of learning

04 Role of transversal skills

05 Role of job-specific skills

06 **Productivity of skills**

07 Outcomes of skills

This policy brief discusses findings related to **Productivity of skills** at the analysis level **persons**. For further publications and multimedia material related to the project, please visit www.lllightineurope.com