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What do employers pay for employees' complex problem solving skills?

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We estimate the market value that employers assign to the complex problem solving (CPS) skills of their employees, using individual-level Mincer-style wage regressions. For the purpose of the study, we collected new and unique data using psychometric measures of CPS and an extensive background questionnaire on employees' personal and work history. The data were collected in 16 firms (23 establishments) in Germany, Spain, South Africa, Denmark, Slovakia, Switzerland, and France in the period 2012–2014. We find significant economic returns to CPS in our sample. One standard deviation higher CPS is associated with 10–20% higher hourly wages. The returns to CPS are sizeable even after controlling for fluid intelligence, suggesting that CPS probably captures skills important for modern production that are beyond what general intelligence tests can measure.

Keywords: complex problem solving skills; returns to skills; wages

Today in developed economies few will disagree that investing in your cognitive skills is a good idea. Among other factors, complementarities between technological innovation and cognitive skills have increased the demand for these skills and with that the returns to the investments in such skills (Autor, Levy, & Murnane, 2003; Spitz-Oener, 2006). In a recent study for instance, Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) show significant returns to cognitive (numeracy and literacy) skills in 23 OECD countries. On average, one-standard deviation increase in numeracy skills is associated with an 18% wage increase among prime-age workers. Cognitive skills, however, are a very broad category and findings of this kind do not inform us if studying theory of music for a year is a better investment than a year of philosophy studies. While this article will not be able to entirely answer that question either, we hope that it will bring us closer to answers of this kind by understanding the role that more specific cognitive skills play in what makes us productive in today's jobs.

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In this article we will estimate the market value of Complex Problem Solving (CPS) skills. In layman's terms, CPS are cognitive skills that assist us in resolving problems which lack transparency in terms of the goals that should be achieved, the barriers which need to be overcome and the means by which we can achieve the goals. Such skills assist us in learning new technologies, addressing a scientific question or act upon an unexpected shock to our immediate environment.

Data on CPS skills for working adults nowadays is still scarce. As a result, to the best of the authors' knowledge, no previous studies have assessed the wage returns to CPS. The closest to our study is probably the one by Hanushek et al. (2015). This study estimated the returns to problem solving in technology rich environments (PS-TRE) and found sizeable positive returns to PS-TRE. The measure of PS-TRE however, should not be confused with the measure of CPS. PS-TRE is designed to assess people's ICT skills and not domain-general problem-solving skills (OECD, 2012).

We estimate that the employees having one standard deviation higher CPS earn between 10 and 20% higher wages. Controlling for intelligence in the same linear regression decreases the effect of CPS on wages by one third, but the returns to CPS still remain statistically significant. These results suggest that CPS skills have an important role in determining earnings in the surveyed countries.

The article has the following structure. Section 1 presents our conceptual framework, defines CPS and discusses the relation between CPS and fluid intelligence. Section 2 explains the data collection and the final sample. Section 3 presents the descriptive results, while Section 4 presents the results of estimating the Mincer regressions. Section 5 concludes.

1. CPS skills, intelligence, and the measurement of their returns

Labour economics has a long tradition of measuring the returns to skills. This literature has been overwhelmingly focused on measuring the returns to education (e.g. Mincer, 1974) and work experience (e.g. Topel & Ward, 1992), because these variables are easy to measure. However, more recent studies find that cognitive abilities rather than education itself are the main determinants of individual wages (Hanushek & Woessmann, 2008; Murnane, Willett, & Levy, 1995). Moreover, further studies evidence that socio-emotional skills, physical and mental health, perseverance, attention, motivation, and self-confidence are as important as cognitive skills in determining economic outcomes (Heckman, 2008; Heckman, Stixrud, & Urzua, 2006). To the best of our knowledge, there is no previous study that has studied the returns to CPS skills.

1.1. CPS skills

Problem solving is the process of searching for an operation or a series of operations in order to transfer the actual state of the system (i.e. the problem situation) into a goal state (Newell & Simon, 1972). In *complex* problems, the goal is not always straightforward. A person can be confronted with a number of different goal facets that he or she needs to weight and coordinate. The term *complex* refers to the system at hand and the complexity of a system increases with the number of its elements and relations (Dörner, 1989).

In dealing with such complex systems, CPS skills can thus be thought of as the skills that facilitate the processes with which an individual aims to control a previously unknown and complex system and to achieve desired goals (Fischer, Greiff, & Funke, 2012). The process of CPS consists of two phases: knowledge acquisition and knowledge application (Fischer et al., 2012, p. 36). The term *complex* refers to the system at hand. The complexity of a system increases with the number of its elements and relations (Dörner, 1989). *Problem solving* is the process of searching for an operation or a series of operations in order to transfer the actual state of the system (i.e. the problem situation) into a goal state (Newell & Simon, 1972).In complex problems, the goal is not always straightforward. A person can be confronted with a number of different goal facets that he or she needs to weight and coordinate. A typical example of CPS is dealing with a new device to send out a text message: it requires exploring features, understanding the system (knowledge acquisition) and manipulating it in such a way that the goal of sending a short message is achieved (knowledge application).

1.2. Conceptual framework

We think of CPS skills as skills that directly contribute to labour productivity. This is because such skills enable a worker to come up with better and more accurate solutions to problems that arise in daily work tasks. In this case, employees demonstrating higher CPS skills will earn higher wages *ceteris paribus*. The contribution to wages that can be attributed to CPS will then be referred to as *returns to CPS*.

In order to estimate the returns to CPS, we employ the most widely used empirical earnings equation—the Mincer equation. The equation can be motivated by output and labour demand functions that are increasing in human capital, such as the human capital production function proposed by Griliches (1977):

$$Y_{\mathrm{i}} = p_{\mathrm{h}} H_{\mathrm{i}} \exp(u_{\mathrm{i}}), \tag{1}$$

where Y_{i} is earnings, p_{h} is price of human capital H_{i}, and u_{i} is the disturbance which represents all other factors that affect Y_{i} and are uncorrelated with H. Individual observations are indexed by i. By assumption, u has zero mean and is independently distributed. Human capital can be thought of as knowledge, skills and abilities that people have and which firms can employ in the production of goods and services. The human capital production function takes various inputs, such as initial ability, schooling time, family background, on-the-job training and others, and translates them into an index of the quality of labour. It is typically assumed that various inputs enter multiplicatively, meaning that exponentiating the terms on the right hand side of the equation results in a better model fit than simply adding them without any transformations. Combining the multiplicative terms allows us to write

$$H_{\mathrm{i}} = \exp(S_{\mathrm{i}} + x_{\mathrm{i}} + x_{\mathrm{i}}^2) \exp(v_{\mathrm{i}}). \tag{2}$$

Here S is years of schooling, x is experience, which enters the equation in order to account for such influences as training or learning by doing, and v is a

disturbance term. Taking logs of (1) and substituting (2), we obtain the standard Mincer equation:

$$\ln Y_i = \alpha + \rho S_i + \beta_1 x_i + \beta_2 x_i^2 + u_i + v_i, \tag{3}$$

where is ρ the *rate of return to schooling* and β specify the returns to work experience. The quadratic term in x allows that conditional on other variables, the returns to work experience are positive but diminishing with experience. This kind of specification of the log wage relation has been found to be quite robust in numerous empirical studies ever since it was introduced by Mincer (Lemieux, 2006). However, as discussed earlier in this section, schooling and experience do not fully capture the scope of skills and abilities that employers pay for. We can therefore extend the model in Equation 3 to account for more specific types of skills or abilities. Since our focus is on CPS skills, we extend Equation 3 to include the CPS term:

$$\ln Y_i = \alpha + \gamma \mathrm{CPS}_i + \rho S_i + \beta_1 x_i + \beta_2 x_i^2 + \varepsilon_i, \tag{4}$$

where the disturbance term ε accounts for other non-systematic factors of variation in log wages. Note that there are several potential ways that Equation 4 may be misspecified. First and foremost, our measure of CPS may imperfectly summarize the difference in the quality of labour other than that which is due to education and work experience. Thus the disturbance term ε may contain variation that is attributed to unobservable ability that may be correlated with some of the regressors, in particular CPS. This will bias our estimate of γ—the returns to CPS skills. We can try to address this problem by controlling for additional variables such as fluid intelligence and personality. The other issue is a measurement error in the regressors. Measurement error in CPS will attenuate the estimate of the returns to CPS. Moreover, the attenuation of the coefficient will be stronger when adding further controls to Equation 4 which are correlated with CPS (see Griliches, 1977) but do not affect wages directly, for example when employers *only* value education because it fosters problem solving skills. We will therefore work with two baseline specifications. In the first specification, we will assume that education has no independent effect on wages other than the accumulation of skills that are measured by CPS:

$$\ln Y_i = \alpha + \gamma \mathrm{CPS}_i + \beta_1 x_i + \beta_2 x_i^2 + \delta' z + \eta_i, \tag{5}$$

where γ measures the returns to CPS and z is a vector of individual-specific controls such as gender, personality, managerial responsibilities and the country of the workplace. We are aware that this specification is likely to overstate the returns to CPS, as educational attainment may have an independent effect on wages, for instance through signaling of higher ability (Spence, 1973) and through the returns to social capital (Glaeser, Laibson, & Sacerdote, 2002).

The second specification assumes that both education and CPS have direct effects on wages, and it is equivalent to (4) with added controls such as gender or country of work.

$$\ln \mathrm{Y}_i = \alpha + \gamma \mathrm{CPS}_i + \rho \mathrm{S}_i + \beta_1 \mathrm{x}_i + \beta_2 \mathrm{x}_i^2 + \delta' \mathrm{z} + \upsilon_i. \tag{6}$$

As explained earlier, these models may understate the returns to CPS as a result of measurement error. We will try to address this problem in Section 4.2 by allowing measurement error in CPS.

1.3. Returns to CPS vs. returns to intelligence

Typically, scholars in the field of economics do not make fine distinctions between different types of cognitive abilities. Scholars in the field of cognitive psychology, however, argue that CPS is a construct which is distinct from reasoning or fluid intelligence (Wüstenberg, Greiff, & Funke, 2012). Funke (2012) for instance argues that the disappointingly low explanatory power of intelligence when it comes to individual economic success was one of the reasons why cognitive psychology introduced alternative measurements of problem solving. One of the main differences between the two constructs seems to be the emphasis on operative intelligence in the case of CPS (Dörner, 1986; Putz-Osterloh, 1981). According to these authors, in comparison to intelligence test performance, CPS test performance is influenced by additional cognitive aspects such as: the search for relevant information; circumspection (e.g. anticipation of future and side effects of interventions); greater relevance of prior knowledge[1] and the ability to organize cognitive operations (e.g. knowing when to do trial-and-error and when to systematically analyse the situation at hand, when to use exhaustive algorithms and when to rely on heuristics, etc.) to name a few. Nonetheless, it is not clear whether these differences matter for capturing the aspects of employees' cognition that affect their productivity. It might be that intelligence tests, which are more oriented toward the measurement of problem solving outcomes and less so toward the operational aspects of problem solving, capture equally well the ability of employees to perform well at their jobs.

In order to investigate the usefulness of introducing a new cognitive concept in economics, we will introduce variants of models (5) and (6), for instance, by substituting CPS with intelligence and by introducing intelligence as an additional factor in the log wage equation. Based on discussion above on the differences between intelligence and CPS we expect that CPS has an independent effect on wages even after controlling for intelligence, if employers observe and care about operative knowledge. However, we have no a priori reason to believe that they do so; hence, our task has exploratory nature.

2. Data collection and sample

2.1. Data collection

The data used in this paper are the first data on CPS skills collected on adult employees at their jobs. The data were collected in the course of the LLLight'in'Europe FP7 (http://www.lllightineurope.com) project. Each data collection session was composed of three parts: (1) CPS assessment, (2) background questionnaire (BQ), and (3) IQ test.

(1) In the first part, CPS skills are measured in so-called MicroDYN and MicroFIN computer-based test environments. The main difference between the

MicroFIN and the MicroDYN is their operating principle. MicroDYN, as introduced by Funke (2001), is based on structural equations, while MicroFIN on finite state automata. Recent evidence suggests that the measures resulting from MicroFIN assessments converge to the same latent dimensions as MicroDYN (Greiff, & Fischer, et al., 2013; Neubert, Kretschmar, Wuestenberg, & Greiff, 2014). The reliability and validity of MicroDYN and MicroFIN have been extensively discussed and tested (see e.g. Greiff, Wustenberg, & Funke, 2012; Wüstenberg et al. (2012); Greiff, & Wüstenberg, et al., 2013; Kretschmar, Neubert, & Greiff, 2015). In our final sample, almost all (398 observations) come from MicroFIN assessments. Part of these (194 observations) also has MicroDYN scores.

In both MicroFIN and MicroDYN subjects are asked to interact on an iPad and solve presented problems which can have different levels of complexity. In the first phase of exploration and knowledge articulation participants explore the relations between input and output and draw connections and links between the variables based on the knowledge that is being acquired. In the second phase the individuals are asked to reach a certain output goal by changing the input values. An example of a microworld story is, for instance, learning how to control outcomes such as the gasoline consumption and the speed of a motor bike.

(2) During the same test session, a BQ was administered to the participants. The questionnaire borrows questions from a selection of previously conducted surveys such as the Adult Education Survey (Eurostat, 2010), the Adult Literacy and Life-skills (OECD & Statistics Canada, 2005), the International Adult Literacy Survey, the Labour Force Survey (Murray, Kirsch, & Jenkins, 1997), the Strategic Learning Assessment Map and the Programme for the International Assessment of Adult Competencies (OECD, 2013). The employee version of the BQ asks questions about basic demographic characteristics, education, employment status, earnings and personality characteristics among many others. The aim of the questionnaire is to capture a history of personal skill acquisition, as well as to measure individual productivity and personality.

(3) In a sub-sample of participants (about half of our sample), a third instrument was used: Raven's test (Raven, Raven, & Court, 2000), a popular non-verbal IQ test. The Raven's Standard Progressive Matrices (SPM) test is a widely recognized and validated instrument to test non-verbal intelligence. For our purposes, the results of the IQ test with Raven's SPM is referred to as 'reasoning score'.

The data were collected in the period 2012–2014 from employees of 16 companies in 23 different locations: Denmark (1), France (1), Germany (10), Slovakia (3), South Africa (2), Spain (5) and Switzerland (1). The average number of employees per location was 19. Most companies are service companies (11), followed by manufacturing (4), and followed by agriculture (1). Tests were carried out on the companies' premises under the supervision of a trained psychologist, lasting on average about 2.5 h. They were administered in the official language of the country where the company premises were located.Test persons participated on voluntary basis and the research team ensured anonymity during the whole process.

2.2. Sample

The currently available sample contains 670 observations, which belong to three major employment groups: employees, trainees, and entrepreneurs. The last two groups constitute 25% of all observations and were excluded from the analysis, because wage data were either not available or not comparable (e.g. in the case of trainees). This reduced our sample to 506 observations. Due to missing values for either net monthly income or CPS, we had to additionally exclude 48 observations, or about 10% of the data on employees. We also dropped 12 observations that had missing values of age, gender, or education. This data cleaning ensures that the sample size stayed the same for different specifications of the Mincer regressions. We furthermore restricted variation in the hourly wage rates to range between 2 and 50 euro/hour after inspecting the wage distributions in the sampled countries. This restriction mainly affects a few extremely well paid persons whose wages can be poorly explained by factors that enter the Mincer equation, such as education, experience or IQ. Finally, we excluded 25 individuals with less than 20 or more than 95 working hours per week in order to reduce the influence of the level of employment on hourly and monthly wages. Part-time workers are often paid a lower hourly rate then full-time workers. Therefore, focusing on full time employees reduces the heterogeneity of workers stemming from factors that are not of interest for this study. We also excluded four more observations where we suspect mistakes in data entry. Our final sample has 399 observations. In this sample, intelligence scores are available for 217 observations, because the intelligence tests were conducted on a subset of participants only.

2.3. Transformation of variables

The CPS score is determined as follows. In every CPS assessment phase, a test taker can score either 0 or 1 for each microworld, depending on successfully completing a task. The sum of microworld scores in a phase is the test taker's score for that phase. CPS score is measured as the sum of standardized scores of two separate phases: knowledge acquisition and knowledge application phase. In our data, we do not find that individual CPS scores perform better in predicting wages compared to the combined score. We rescale CPS scores, so that the sample mean and standard deviation are 0 and 1, respectively. The intelligence variable is obtained by normalizing standardized Raven's reasoning test scores. We use non-age adjusted intelligence scores. These transformations help us obtain a unit measurement that is easier to interpret—standard deviation, for constructs that do not have a natural unit of measurement. At the same time, the transformation does not affect the distributional properties of the measures.

We compute hourly wages from net monthly salary and actual working hours. Since the data-set includes observations from non-euro zone countries (in particular, Denmark, South Africa, and Switzerland) we convert all values into euro using official exchange rates. For the regression analysis, we transform hourly wages by taking the natural log. After transforming, the regression coefficients show the percent difference in wages for a unit difference of a variable.

Further important variables for estimating the Mincer equations are: educational attainment, gender, supervisory responsibilities, and work experience.

Educational attainment is measured using the International Standard Classification of Education (ISCED). We distinguish the following six categories of educational attainment: 1–2 (primary school or less), 3 (lower secondary including vocational), 4 (secondary including vocational), 5B (technical and applied tertiary education), 5A (theoretical tertiary education) and 6 (PhD or doctoral studies). Supervisory responsibility is measured with the following question: 'In your job or jobs, do you have any supervisory responsibilities? If yes, how many people work under your supervision?' The response categories are: None, 'Between 1 and 3', 'Between 4 and 10', 'Between 11 and 10', and 'More than 20 people'. Work experience is measured in years spent in employment and is self-reported. We additionally collected data on personality traits using Big 5 measures (Costa & McCrae, 1992; Rammstedt, 2007; Rammstedt & John, 2007). With the current sample, we do not find any effects of personality on individual economic outcomes. We therefore abstain from discussing the influence of personality on wages in the rest of the article.

3. Descriptive results

Of all participants, 41.4% are female. The average age of our participants is 41 and the average work experience is about 15 years (see table 1). Of all participants, 56% do not have any supervisory responsibilities, while 44% have at least some. Most employees (72%) have some type of tertiary degree, while 28% have secondary education or less. Our sample is therefore biased toward individuals with higher skills. This may result in a positive bias in our estimates of the returns to CPS, because the returns to cognitive skills are higher in highly-skilled occupations (Autor & Handel, 2013). In order to be able to make a more general statement about our findings, we create probability weights specific to educational groups, using the known distributions of education by country as explained in subsection 4.4 below.

Table 1. Summary statistics of the variables

Variable	Mean	SD	Min	Max	Obs
lnwage	2.35	.65	.73	3.78	399
CPS	.00	1.00	−2.43	1.81	399
Workexp	15.41	9.63	.00	42.00	399
Intel	.00	1.00	−1.87	1.93	217
Age	41	10	20	65	399

Notes: lnwage = natural log of the hourly wage, CPS = complex problem solving skills, Workexp = work experience measured in years, Intel = Raven's test of fluid intelligence, age measured in years.

Table 2. Correlations between CPS and main wage regression variables

Log Wage	Work experience	Gender	Education	Intelligence
.357***	−.364***	.342***	.438***	.617***

Notes: ***Statistically significant at 1% or better. For factor variables, R^2 is presented instead. Adjusted for country differences.

Table 2 shows the partial correlations (after controlling for country-specific effects[2]) between CPS and the variables that enter the baseline models of the Mincer equations. CPS correlates positively with wages ($r = .36$). It correlates negatively with work experience ($r = -.364$). This latter correlation is negative mainly because of the correlation between CPS and biological aging and the fact that work experience correlates strongly with age. CPS is also significantly and positively correlated with gender and with the level of educational attainment. Finally, CPS is highly positively correlated with fluid intelligence as measured by Raven's reasoning test ($r = .62$).

4. Results

We now turn to our estimations as discussed in subsections 1.2 and 1.3. We first present the baseline results, followed by an analysis of the causal interpretation of our results and followed by a discussion of the results concerning the relation between CPS, fluid intelligence, and wages.

4.1. Baseline results

We start by presenting the results of estimating our baseline models, Equations 5 and 6. We rewrite these baseline equations to reflect the characteristics of our data:

$$\ln Y_{\mathrm{i}} = \mathrm{const} + \gamma \mathrm{CPS_i} + \beta_1 \mathrm{Workexp_i} + \beta_2 \mathrm{Workexp_i^2} + \delta' \mathrm{z} + \varepsilon_{\mathrm{i}} \tag{7}$$

and

$$\begin{aligned} \ln Y_{\mathrm{i}} &= \mathrm{const} + \gamma \mathrm{CPS_i} + \lambda' \mathrm{ISCED} + \beta_1 \mathrm{Workexp_i} + \beta_2 \mathrm{Workexp_i^2} + \delta' \mathrm{z} + \eta_{\mathrm{i}} \\ \mathrm{i} &= 1, \ldots \mathrm{n} \end{aligned} \tag{8}$$

where the subscript i indicates that our variables are measured for each individual i of our sample with size n. ISCEDis a set of six dummies for six levels of educational attainment as discussed in Section 2. Workexp is total work experience (measured in years). z is a matrix of individual controls such as country of the establishment, gender, or supervisory responsibilities, and ε and η are the error terms of Equations 7 and 8 subsequently. γ is our coefficient of interest, because it measures the wage returns to CPS. It is interpreted as the percentage of increase in wages that corresponds to one standard deviation increase in CPS.

We estimate these models using ordinary least squares (OLS). It is important to mention that all regressions presented below control for country fixed effects, meaning that the identifying variance for the effect of CPS on wages stems from within-country differences.

Table 3 shows the results of these estimations. Model 1 estimates the standard Mincer model as described in Equation 3, Section 1.2. All variables contribute to the explanation of individual wages in line with previous findings (e.g. Lemieux, 2006): wages increase at a decreasing rate with work experience; wages grow with educational attainment, and males earn significantly more than females. The fit

Table 3. Returns to CPS, baseline estimates

	Model 1	Model 2	Model 3	Model 4
Workexp	.032***	.038***	.034***	.031***
	(.006)	(.006)	(.006)	(.006)
Workexp^2	−.001***	−.001***	−.001***	−.001***
	(.000)	(.000)	(.000)	(.000)
ISCED3	.135		.12	.109
	(.058)		(.057)	(.057)
ISCED4	.368***		.309**	.315**
	(.079)		(.081)	(.082)
ISCED5B	.448***		.380***	.383***
	(.075)		(.074)	(.073)
ISCED5A	.662***		.557***	.537***
	(.053)		(.06)	(.06)
ISCED6	.783***		.650***	.630***
	(.065)		(.071)	(.075)
Male	.180***	.118**	.121**	.112**
	(.043)	(.047)	(.046)	(.046)
CPS		.200***	.103***	.103***
		(.026)	(.028)	(.028)
Supervise 1–3 people				.021
				(.044)
Supervise 4–10 people				.079
				(.057)
Supervise 11–20 people				.196**
				(.074)
Supervise over 20 people				.170**
				(.068)
(Intercept)	2.123***	2.721***	2.209***	2.213***
	(.118)	(.109)	(.119)	(.128)
R^2	.754	.713	.765	.774
Adj. R^2	.745	.706	.756	.762
Num. obs.	399	399	399	399
df	384	388	383	379
Mean dep. var	2.346	2.346	2.346	2.346
BIC	329	366	317	325
S.E.R.	.33	.355	.323	.319

Notes: Results from OLS models. The explanatory variable is the natural log of wages. Significant at: ***$p < .001$, **$p < .01$, *$p < .05$. Robust standard errors in parentheses. *Abbreviations*: CPS, complex problem solving skills; df, degrees of freedom; BIC, Bayesian Information Criterion; S.E.R., standard error of regression. Country dummies are used as controls in all regression models. ISCED: 1–2 (primary school or less) is the reference category, 3 (lower secondary including vocational), 4 (secondary including vocational), 5B (technical and applied tertiary education), 5A (theoretical tertiary education) and 6 (PhD or doctoral studies). Refer to subsection 2.3 for further definitions of the variables.

of the model is very good—these variables explain 75% of the variance in hourly wages in our sample.

Model 2 estimates our first baseline model for CPS, following Equation 7 in this section. We find that one standard deviation higher CPS corresponds with 20% higher wages, which is a very large effect in monetary terms.[3] The inclusion of CPS also improves the model fit slightly, by 1%. The primary reason for only a small improvement in R^2 is the high correlation between CPS and other explanatory variables that appear in the regression, in particular education and

gender. Adding CPS as a covariate does not add much to the overall model fit, but it takes away about 15% of the explanatory power of education and about one third of the explanatory variable of gender once included in the regression. The finding that the explanatory power of education is reduced when controlling for direct measures of skills is in line with the findings of Hanushek and Woessmann (2008), who claim that firms value cognitive abilities, and that these are sometimes more and sometimes less related to education, depending on its quality. The effect of the CPS coefficient on the coefficient of gender suggests that males perform better in problem solving than females.

As discussed in subsection 1.2 (Equation 6), not including controls for educational attainment is likely to induce an upward bias in γ. Model 3 of table 3 includes both CPS and ISCED dummies in the estimation. This model is equivalent to the second baseline model, Equation 8. As expected, the coefficient of CPS is now reduced significantly. In fact, according to this specification, one standard deviation higher CPS corresponds to 10% higher hourly wages, only half of the estimate in Model 2. We take this estimate as the lower bound of γ.

Finally, some may argue that our wage regressions may be misspecified unless we control for the fact that employees with managerial responsibilities earn a premium for taking such responsibilities. This would be particularly problematic in the case of a positive correlation between CPS and managerial responsibilities, e.g. because better problem solvers become managers. This is why Model 4 additionally controls for supervisory responsibilities. As expected, there is a significant wage premium associated with supervisory responsibilities, in particular for those managing more than ten employees. Evidently, however, the coefficient of CPS remains intact by this control, which suggests that this variable affects wages independently of CPS.

4.2. Instrumental variable approach

As argued earlier, our estimates of CPS may be attenuated towards zero as a result of measurement error. One way to correct for measurement error in variables is using the instrumental variable (IV) approach (Griliches, 1977, 1986). As long as the candidate IVs are independent from the regression disturbance term, the IV approach provides a consistent estimate of the coefficient of the variable measured with error by isolating the variation to the subspace spanned by the instruments. We employ an IV approach commonly used in labour economics, two-stage least squares (2SLS). 2SLS is a two-stage estimation procedure. In our case, the first stage is OLS estimation where the dependent variable is CPS and the independent variables are all independent variables that enter Equation 8, except for CPS, plus a so-called IV, which we explain below. The second stage of the estimation is again an OLS regression, where log wage is our dependent variable and the Mincerian regressors are our independent variables. However, the crucial difference from Equation 3 is that our direct measure of CPS is replaced with the predicted CPS from the first stage of 2SLS estimates. CPS by construction isolates part of the variation in CPS that can be assigned to factors that do not directly affect wages, but only affect wages through CPS. As such it has less variation than the original measure of CPS, meaning that it is less efficient, which is reflected in higher standard errors for the coefficient of CPS.

The IV is a variable that itself does not have a direct effect on wages, but affects the level of CPS. It is allowed that the IV affects wages indirectly through CPS. Primary and secondary school grades and in particular performance in mathematics are promising IVs for the measurement error problem. Grades are good indicators of early age cognitive ability, and pupils who have higher grades, in particular higher grades in math, are expected to perform better in school. In our sample, self-reported average grades and math grades are highly correlated with CPS scores ($r = .33$ and .36, respectively). At the same time, we do not expect direct effects of school performance variables on wages, as employers are not likely to attach a specific value to them.[4]

Table 4 presents the results of the 2SLS estimates. Because our sample is slightly reduced for this specification due to missing values in the grades variable (377 vs. 399 observations), Model 1 re-estimates baseline Equation 8 for comparison, and Model 2 shows the second stage of the 2SLS results. The sample reduction has no impact on the size of the CPS coefficient. The 2SLS results in Model 2 suggest that indeed measurement error attenuates the effect of CPS on wages. This estimate suggests far larger effects of CPS on wages: one standard deviation higher CPS corresponds with 29% higher wages. This estimate is statistically different from the estimate of the baseline Equation 8 (i.e. Model 3 in table 4), but due to the large standard error of the CPS coefficient we cannot

Table 4. Returns to CPS, instrumental variable approach

	Model 1 (OLS)	Model 2 (2SLS)
Workexp	.034***	.038***
	(.006)	(.008)
Workexp^2	−.001***	−.001**
	(.000)	(.000)
Male	.115**	.015
	(.048)	(.064)
ISCED3	.111	.086
	(.059)	(.08)
ISCED4	.312**	.213
	(.083)	(.11)
ISCED5B	.365***	.250*
	(.077)	(.106)
ISCED5A	.546***	.357**
	(.063)	(.122)
ISCED6	.641***	.412*
	(.073)	(.145)
CPS	.103***	.285***
	(.03)	(.092)
(Intercept)	2.219***	2.363***
	(.125)	(.146)
R^2	.756	
Adj. R^2	.746	
Num. obs	377	377
df	361	361
Mean dep. var	2.337	2.337
S.E.R.	.328	.351

Notes: Results from OLS and 2SLS models. The explanatory variable is the natural log of wages. Significant at: ***$p < 001$, **$p < .01$, *$p < .05$. Robust standard errors in parentheses. Please also refer to Table 3 notes.

say that it is statistically different from the estimate obtained from estimating the baseline Equation 7 (i.e. Model 2 in table 4). In summary, our 2SLS estimates suggest that the returns to CPS are closer to the returns estimated in baseline model (7), where one standard deviation higher CPS is associated with 20% higher hourly earnings.

4.3. Wages, CPS and fluid intelligence

Our results of estimating the relationship between fluid intelligence and wages, and CPS and wages after controlling for fluid intelligence are presented in table 5. As explained in Section 2, the sample for which we have available estimates of fluid intelligence is significantly smaller—217 observations. Halving the sample size will substantially affect the precision of our estimates, thus these results should be interpreted with caution. Models 1 and 2 mimic our baseline estimates, that is, they re-estimate Equations 7 and 8. Evidently, in this smaller sample, the returns to CPS are significantly smaller and even insignificant when controlling for educational attainment in all variants of Equation 8 (here specifically Model 2). However, it is important to point out that this attenuation of the

Table 5. Returns to CPS vs. returns to intelligence

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Workexp	.055***	.042***	.052***	.041***	.053***	.041***
	(.01)	(.009)	(.009)	(.009)	(.01)	(.009)
Workexp^2	−.001***	−.001**	−.001***	−.001**	−.001***	−.001**
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Male	.066	.066	.112	.072	.067	.066
	(.069)	(.069)	(.064)	(.062)	(.068)	(.068)
CPS	.156***	.056			.105**	.014
	(.038)	(.045)			(.046)	(.05)
ISCED3		.127		.12		.119
		(.095)		(.088)		(.089)
ISCED4		.499***		.505***		.501***
		(.17)		(.17)		(.171)
ISCED5B		.429**		.422**		.415**
		(.129)		(.121)		(.122)
ISCED5A		.570***		.567***		.556***
		(.105)		(.095)		(.099)
ISCED6		.578***		.559***		.550***
		(.124)		(.118)		(.12)
Intelligence			.124***	.067**	.071*	.061*
			(.029)	(.03)	(.035)	(.035)
(Intercept)	2.197***	1.818***	2.257***	1.845***	2.216***	1.847***
	(.077)	(.099)	(.077)	(.094)	(.076)	(.096)
R^2	.745	.793	.742	.797	.751	.797
Adj. R^2	.736	.78	.732	.784	.74	.783
Num. obs	217	217	217	217	217	217
df	208	203	208	203	207	202
Mean dep. var	2.209	2.209	2.209	2.209	2.209	2.209
BIC	199	181	202	177	200	182
S.E.R.	.345	.315	.348	.312	.343	.313

Notes: Results from OLS models. The explanatory variable is the natural log of wages. Significant at: ***$p < .001$, **$p < .01$, *$p < .05$. Robust standard errors in parentheses. Please also refer to Table 3 notes.

coefficients in Model 2 can be attributed to the reduction of the sample size and not to the inclusion of additional controls as demonstrated by the differences between the first two models in table 3 (full sample) and their equivalents in table 5 (smaller sample). It is also important to say that here we are primarily interested in the comparative effects of CPS and fluid intelligence on wages and not between these effects and the one of education.

Model 3 mimics Model 1 in table 5, but replaces CPS with a reasoning score, which is our measure of fluid intelligence. We find that intelligence acts similarly to CPS. Although somewhat smaller, the coefficient of intelligence is statistically indistinguishable from the one of CPS. In terms of the overall fit, Model 3 is not much different from Model 1. We observe a similar pattern when comparing Models 2 and 4. Model 4 estimates baseline model from Equation 8, but replaces CPS with the reasoning score. The magnitude of CPS in Model 2 (5.6%) is similar to the magnitude of reasoning in Model 4 (6.7%), but CPS is not statistically significant. Again, the lack of significance should at least partially be attributed to the sample size restriction, making it difficult to judge the actual difference between these coefficients. Model 5 adds intelligence to our baseline model from Equation 7 (which does not include education as a control), here presented in Model 1. This reduces the coefficient of CPS by one third, but the returns to CPS remain large and statistically significant. In a symmetric manner, adding CPS reduces the coefficient of intelligence from 12.4 to 7.1%. Model 5 suggests that, with respect to wages, CPS adds explanatory power beyond intelligence. Finally, for completeness, Model 6 estimates the effects of CPS and intelligence in one model, but additionally controlling for educational attainment (baseline Equation 8). As anticipated, in this specification we find no effect of CPS on wages, partially due to the sample size problem and partially due to the attenuation which reasoning causes upon the effect of CPS on wages.

Should we conclude from these estimates that CPS does not have an effect on wages once we properly control for reasoning and education? Our answer is that such conclusion would be premature and unfair to the strong partial correlations we find between CPS and wages in all previous estimates with a larger sample. Moreover, the causalities between fluid intelligence, CPS and education are way more complex than what we model in our simple regression models. The take away of this exercise should rather be that the positive relation between CPS and wages is attenuated but the effect does not vanish when controlling for fluid intelligence in the regressions.

4.4. Non-representative sample: results with probability weights

As discussed in Section 2, our sample includes disproportionally many highly-skilled individuals. This may induce an upward bias in our estimates if the returns to CPS in jobs that highly skilled perform are systematically higher than those in low skilled jobs. To learn about the true educational distribution of the population in an area that includes the countries that we sampled, we have used the Labour Force Surveys of the included countries. Based on the discrepancies between the true distribution of educational attainment and that in our sample we create probability weights that allow adjusting the estimation procedure to correct the sampling bias. Table 6 shows the re-estimates of our baseline models (Equations 7 and 8, subsection 4.1) after weighting. Model 1 suggests that our

Table 6. Returns to CPS, results with probability weights

	Model 1	Model 2
Workexp	.022***	.022***
	(.006)	(.005)
Workexp^2	.000*	.000**
	(.000)	(.000)
Male	.209***	.170***
	(.059)	(.058)
CPS	.184***	.098**
	(.025)	(.023)
ISCED3		.086*
		(.046)
ISCED4		.290***
		(.075)
ISCED5B		.368***
		(.066)
ISCED5A		.507***
		(.052)
ISCED6		.617***
		(.065)
(Intercept)	2.785***	2.318***
	(.116)	(.118)
R^2	.848	.884
Adj. R^2	.844	.879
Num. obs	378	378
df	368	363
Mean dep. var	2.283	2.383
BIC	381	309
S.E.R.	.271	.238

Notes: Results from weighted OLS models. The explanatory variable is the natural log of wages. Significant at: ***$p < .001$, **$p < .01$, *$p < .05$. Robust standard errors in parentheses. Please also refer to Table 3 notes.

earlier estimation of baseline Equation 7, presented in table 3, Model 2, overstates the effect of CPS on wages by 1.6%. This difference is within the standard error. The estimation of baseline Equation 8, presented in table 3, Model 3, is practically indistinguishable from the weighted estimation with the difference in the value of the coefficient of just .5%. We can therefore conclude that OLS estimates of the effect of CPS on wages are not substantially affected by sample selectivity.

5. Conclusions and discussion

While the literature measuring the returns to education and skills in general is broad, there exists only scattered evidence about the returns to more specific skills. Nowadays only few would dispute the fact that investing in more education and more skills is a good choice in life. However, we do not have a good understanding about the kinds of skills we should invest in. This study hence looks at a more specific type of skills—CPS skills and estimates what employers' pay for employees' CPS skills.

The contribution of this article to the literature is twofold. First, this is the first article to estimate the returns to CPS skills. Our findings suggest that there is a

sizable premium to these skills. While the range of the estimated wage returns is wide and dependent on the sample size and the included controls, in the main models, one standard deviation higher CPS corresponds with 10–20% higher wages. This means that employers recognize CPS and are willing to pay higher wages to employees who have these abilities. These results are even stronger when using IV approach to correct for measurement error and they are not sensitive to the use of probability weights which correct for the non-representative character of our sample. One caveat is that the effect of CPS on wages vanishes when working with about half of our sample (the part of the sample for which we have measured intelligence), after controlling for education. However, evidently this is due to the halving of the sample size and not due to the lack of an actual relationship.

Second, we show that CPS has an effect on wages that is independent from the wage effect of fluid intelligence. CPS and fluid intelligence are highly correlated and when used interchangeably in wage regressions, they rendered comparable results. Including both CPS and intelligence in the same wage regression reduced the effect of CPS on wages by one third. However, both intelligence and CPS remained sizeable and statistically significant. The effect of CPS on wages vanishes in our strictest models which only use half of the sample size and include both education and intelligence in addition to other controls. In this model however it is difficult to tell how much of diminishing of the effect is caused by the halving of the sample size, and how much by the actual attenuation that education induces on CPS.

CPS is strongly correlated with educational attainment. The inclusion of CPS in the standard Mincer regression reduces the size of the estimate of the effect of educational attainment by about 15%. Educational attainment, on the other hand, halves the coefficient of CPS in the wage regressions. This dependency suggests that education and CPS are causally dependent. Future research should address the causality between the two. This also reveals some of the limitations of the current article. To this end we do not understand the causal relationships between CPS, intelligence, education and other components of human capital. Moreover, while we strive to make a general statement about the effect of CPS on wages using an international sample of employees, our data pool is modest and a number of countries are represented with only few observations. We address this problem by constructing probability weights and re-estimating our models using the reweighted sample, but we are aware that this shortcoming is best addressed by expanding the sample. High on the agenda for future research is to understand how CPS is being acquired over the lifetime. To what extent do parental education, formal education and on the job learning affect CPS? Can CPS be developed via on-the-job training? Answers to such research questions would enable us to derive recommendations for education policy and personnel management.

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Notes

1. This claim is disputed among the scholars in the field. For instance, Wüstenberg et al. (2012) argue that the MicroFIN and MicroDYN measures of CPS are designed such as to minimize the influence of prior knowledge.
2. We control for country effects even in the correlation tables because we have an international sample with wide cross-country variance of wages. Moreover, certain types of industries which pay high wages cluster by country such as IT firms in Germany. Not controlling for country effects induces spurious relationships between our independent variables and wages.
3. We also find evidence of mild curvature in the returns (not reported here), corresponding to about 1–2% difference in returns between high CPS individuals and low CPS individuals.
4. It may be argued that grades serve as a signal of ability and for this reason are important for employers. While this may be true, school grades are not a final record of academic performance of most individuals in our sample.

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