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Abstract

This paper investigates to what extent education is rewarded on the labour market because of the cognitive skills it indicates, using IALS data for the United States, the United Kingdom, Germany and the Netherlands. By empirically distinguishing between general cognitive ability and work-specific cognitive ability, we show that the cognitive component of schooling is larger than anticipated by Bowles and Gintis (2000; 2002). Instead of around 20 percent of the education effect being cognitive, our results indicate that between 23 and 53 percent of the education effect is cognitive, depending on the country and operationalization of cognitive skills. Moreover, it was shown that the relative importance of general versus work-specific cognitive abilities varies systematically between countries, with a larger fraction of the schooling effect being captured by the work-specific component in Germany and the Netherlands than in the US and the UK. This is explained by the different role of schooling between countries. Importantly, controlling for allocative processes related to the industry, organization and occupation of employment was particularly relevant in Germany, which supports the notion that this country is most credentialized.

INTRODUCTION

Schooling is the single-most important determinant of labour market opportunities in modern, western countries. The reason *why* education is so influential is, however, far from clear. Several mechanisms have been proposed to explain why people of higher levels of schooling have better labour market opportunities than people with lower levels of schooling. On the one extreme, human capital theory assumes that education provides productive skills to individuals, and employers are willing to reward productivity (Becker 1962, 1976). On the other extreme there are theories arguing that there is no productivity argument involved; education is just used as a legitimized means for social closure and exclusion (Collins 1979). In between there are several theories proposing that education may not provide ready-to-use skills but indicates potential productivity or trainability on which applicants are screened (Arrow 1973; Spence 1973; Thurow 1975).

Disputing the single-sided emphasis on productive skills of human capital theory, Bowles and Gintis (2000; 2002; Bowles et al. 2001) propose the alternative view that education gives an indication of whether potential employees match the employer's incentive-enhancing preferences; traits that "assist in the exercise of the employer's authority" (Bowles and Gintis 2000: 125). Examples of such traits are an inclination to truth telling, an orientation towards the future, and identification with the organization's goals rather than with those of co-workers. Given that less than twenty percent of the schooling effect on earnings is cognitive, according to Bowles and Gintis, such incentive-enhancing preferences could potentially explain much of the remainder of the education effect. This conclusion on the size of the non-cognitive component of schooling is drawn on the comparison of two regression models predicting wages browsed from a large number of empirical studies on the United States: one with and one without a control for cognitive ability, with both including years of education. Because, on average, less than twenty percent of the education effect is reduced by including cognitive ability, the authors conclude that the remainder of the education effect is non-cognitive.

We are generally sympathetic to the claim that non-cognitive skills may play an important role for labour market outcomes, and we regard this hypothesis as a promising opportunity for inter-disciplinary research involving sociologists, psychologists and economists. Moreover, increasing and compelling evidence has been recently accumulated to support this claim. Bowles et al. (2001, 2002) and Heckman et al. (2006) review extensively this literature and provide additional empirical support.

However, before an empirical assessment is made of the returns to non-cognitive components of schooling, we hold it essential to improve on the understanding of the role of cognitive skills first. Therefore, in this paper we want to improve on this in two ways. First, although Bowles et al. (2001: 1157) conclude that "it would be surprising if a general test of cognitive functioning were to alter significantly the conclusions of our survey", we argue that insufficient attention has been paid to a broader measurement of productive skills. Particularly because the human capital model assumes that skills learnt at school are complemented with skills acquired on the job, we should pay due attention to those cognitive qualities that are developed and mobilized at the workplace before we conclude that this approach has limited explanatory power.[1] Moreover, while Bowles et al. (2001:1140) tend to equate the productive skills posited by human capital theory with cognitive ability, we argue that it is rather dubious assumption.

Second, the works of Bowles and Gintis, as well as most studies they cite, pertain to data from the United States. It is plausible that education functions in different ways in different countries (see e.g. Shavit & Müller 1998; Allmendinger 1989; Carbonaro 2006), so the size and the form of the productive skills component of

[1] Also Bowles et al. (2001: 1157) leave room for this possibility, although they tend to emphasize the measurement problems that arise when trying to estimate the role of work-specific skills (see appendix).

schooling may also vary across economically advanced countries.[2] Earlier research has argued that educational achievement is less well linearly measured in many European countries than in the United States. Whereas the uni-dimensional US system grants a reasonable measurement of educational achievement by years of education, many European countries have systems where a variety of numbers of years of schooling could lead to the same final level of schooling, and where a similar number of years of schooling could indicate strongly varying levels of educational attainment (Shavit & Müller 1998; Breen & Jonsson 2000). We argue, and our findings indicate, that human capital-type skills can not be measured equally well on a linear scale in different countries, just as earlier research demonstrated with regard to educational attainment. More specifically, controlling for cognitive skills in order to test human capital explanations may be more appropriate in some countries than in others.

In this paper we intend to elaborate on these two issues by expanding on the list of skills that we take into account, and by expanding the analysis to four countries that vary strongly in the extent the educational system provides productive skills to students: the United States, Britain, Germany, and the Netherlands. This way we intend to answer the questions to what extent the effect of education is due to (a broad set of) productive skills related to schooling, and whether this differs across countries. We will use data from the International Adult Literacy Survey (IALS) gathered in 1994.[3] This dataset has detailed cognitive tests (in language literacy and mathematics), as well as measures on the cognitive skills used in the present occupation. Our main findings are that (1) general cognitive skills explain a larger part of the education effect than shown by

[2] Bowles et al. (2001: 1156) leave room for cross-national variations, but they expect them to be relevant mainly in comparisons between poor and rich countries, rather than *within* the latter. Our analysis is restricted to developed economies, but we agree that the importance of cognitive skills may be greater in less developed countries, as shown for instance by Boissiere et al. (1985).
[3] The data for Britain were collected in 1996.

Bowles and Gintis in all countries (2002); (2) the work-specific cognitive skills explain an additional fraction of the effect of schooling, and (3) the general cognitive skills are a relatively important explanation for the education effect in the United States and the United Kingdom, whereas the work-related cognitive skills are relatively important in Germany and the Netherlands.

The claim that cognitive skills, once properly measured, explain more than is usually found has been made before (Green 2001; Kerckhoff et al. 2001; Denny et al. 2004). Furthermore, we have found in the economic literature a few articles, often based on the IALS data, addressing the issue of cross-country variations in returns to education and to cognitive skills (Denny and Harmon 2001; Denny et al. 2004). The general framework for these analyses is the debate on growing income inequality in the U.S., also relative to European countries. The crucial issue is whether, in a context of rapid technological change and increasing economic interdependence, high and increasing returns to education in the U.S may account for the high and increasing level of income dispersion in this country (Leuven et al. 2004). An alternative hypothesis is that institutional regulations, e.g. collective bargaining, unemployment insurance and job protection legislation, are a more important explanation for both variations across countries and over time (Blau & Kahn 2005; Carbonaro 2006). Hence, the main focus of the economic literature is on the role played by structural factors, or by labor market and welfare institutions, while relatively little attention has been paid so far to the influence of educational institutions. Our paper adds to this literature in that it shows that educational systems differ in the extent to which they sort individuals on different types of cognitive skills, which in turn affects the level and shape of income returns to schooling in each country. The distinction between general and work-specific skills not only shows that cognitive skills are more important than earlier supposed, but also that their role varies across countries in line with what one would expect on the basis of the educational system.

THEORETICAL BACKGROUND

Neo-classical economic theories and their sociological allies

The neoclassical model of the labor market is usually related to sociological approaches that have been labelled functionalist theory, technocratic theory, modernization theory, meritocratic theory, and the liberal theory of industrialism. Both the neoclassical model and these sociological allies share the basic assumption that education indicates productivity relevant for labor market performance.

In the neoclassical model two variants exist. The first one, human capital theory, stresses that people acquire productive skills in school (Schultz 1971; Becker 1976), so that people invest in schooling in order to become more productive and get rewarded for it. The second variant sees education more as a positional good that indicates productivity in an indirect way. Some scholars from this perspective argue that although education does not generate ready-to-use skills, it makes people more easily trainable on the workfloor, thereby reducing training costs (Thurow 1975). Others argue that education is related to cognitive quality because education sorts on variations in intelligence prevalent before school enrolment. In other words, education is an easily observable attribute that is correlated to pre-existing variation in cognitive qualities, thereby enhancing education as a screening device for cognitive skills (Arrow 1973). The training cost model and the screening perspectives differ with regard to the causality between education and cognitive qualities. Arrow's screening perspective is most clear on the causality, where cognitive qualities affect the level of schooling acquired. Thurow clearly leaves more room for the fact that people learn something in school; not productive skills but 'learning skills' that reduce training costs. Spence (1973) developed a similar approach as Arrow when he argued that education functions as a signalling device that is used by employers to reduce uncertainty about applicants' productivity. The fact that Spence distinguishes between signals, which refer to traits that people can change in anticipation of the (wage) returns they lead to, and indices, which refer to unalterable traits such as gender, may imply that his model assumes that education is not solely a consequence of pre-existing variations in skill level, but could also be its cause.

The sociological allies, all from a functionalist stance, similarly assume that education indicates productivity through the cognitive skills associated with it (without being too clear about the causality between the two). The basic argument of the functionalist approaches is that the increased complexity of the labor market requests that selection and allocation is based on educational attainment. This should have led to an increased impact of schooling on labor market outcomes because of 'differential functional importance' of social positions and 'differential scarcity of personnel' for filling up those positions (Davis & Moore 1945: 243-44; Blau & Duncan 1967; Treiman 1970). Thus, the interpretation of this perspective for an increased relevance of schooling for occupational attainment is grounded in the increased complexity of jobs, requiring cognitive skills associated to schooling.

Critiques of the productive skills model of schooling

The explanation for the relevance of schooling of the functionalist and neo-classical models has met a lot of opposition. The criticisms, which originate from various angles, mostly come down to the fact that this view about the role of schooling does not do justice to *allocative mechamisms* on the labor market. The fact that highly educated individuals are often allocated to high-earning jobs is, according to these criticisms, not (only) caused by differential marginal productivity of workers of different skill level, but by various other factors as well. Firstly, Bourdieu's cultural reproduction theory holds that highly educated individuals have mastered acquaintance with the dominant cultural codes in society which gives them an advantage on the labor market (Bourdieu & Passeron 1999). Moreover, by monopolizing the educational system and by organizing it in close resemblance with their own culture, elites have been able to legitimately transmit their advantaged position to their children through schooling. Hence, allocation on the basis of (class-related) cultural capital is essential in this perspective. It should be noted that, in principle, what cultural capital comprises of is arbitrary, as long as it shows affinity with the dominant culture in society (Bourdieu & Passeron 1999; Lamont & Lareau 1988). This arbitrariness puts cultural capital obviously at a long distance from an explanation of the schooling effect that refers to productive skills.

A second (related) perspective that puts allocative mechanisms central in the explanation for the education effect on the labor market is credentialism theory (Collins 1974; 1979; D.K. Brown 1995). Rather than informing employers on productivity, educational qualifications (credentials) are used as a legitimized means for social exclusion and inclusion. The educational system provides formalized credentials that give access to 'political labor' which is not aimed at the production, but at the distribution of resources within organizations. Access to a large number of advantaged occupations is regulated through formal qualification requirements. Collins (1979) is very explicit on the non-productive element of schooling. Based on the empirical findings that people acquire their job-relevant skills mostly on the job rather than in school, that they forget what they learned in school very rapidly, and that productivity of higher-educated workers is not higher than of lower-educated workers holding the same job, Collins rejects the 'technocratic' (human capital) model of schooling and hence denies that education indicates productive skills. Central in the credentialism theory is that education effects on earnings are mainly manifested through the regulated access to *occupations*.

A third domain where criticism towards the productive skills model has been forwarded is the structural stratification literature, which shares some basic assumptions with segmented labor market theory. Both structural stratification researchers and segmented labor market theorists argue that allocation to jobs is not solely explained by human capital theory. There are segments of the labor market where well-paying jobs are situated, and where returns to education are higher than elsewhere. These structural positions are held to vary between primary and secondary segments, between industries, or organizations of different size (Beck et al. 1978; Caroll & Mayer 1986; DiPrete & Grusky 1990; Doeringer & Piore 1971; Stinchcombe 1979 Kalleberg & Van Buren 1996).

Also Bowles and Gintis deny that education is mainly indicating the kind of productive skills posited by human capital theory. In their earlier work Bowles and Gintis argued that social interactions and individual rewards in schools are structured in the same way as workplace interaction takes place, which they called the 'correspondence principle'. For example, students educated at lower levels of schooling have a different authority relation to their teacher than students at higher levels which was meant, according to the correspondence principle, to prepare people for their future worklife relationships with their superiors. In their later work Bowles and Gintis have come back from the passive oversocialized interpretation of mankind which was underlying their model (Mehan 1992), and replaced it with a more agency-based approach that explains cultural processes at school in anticipation of future positions.

The correspondence of school-based culture and future life implied for Bowles and Gintis is the reason why education pays off on the labor market could not be solely attributable to the productive skills education represents according to human capital theory. Comparing wage equations found in the literature with education as a regressor, and education and cognitive skills as regressors in a second model, Bowles and Gintis conclude that around 82 percent of the education effect is non-cognitive. They interpret this finding as evidence against human capital theory and, in line with their model, they propose that the remainder of the education effect could partly be explained by the incentive-enhancing preferences of employers; employers prefer those attributes of applicants/workers that enhance their own authority.

Although similar with regard to the transmission of cultural norms to students, and the class-bias in familiarity with the norms that are transmitted, there are important differences between Bourdieu's cultural reproduction theory and the model of Bowles and Gintis. An important difference with cultural reproduction theory is that cultural capital can be seen as a scarce good, a 'possession', whereas the correspondence principle puts more emphasis on the roles that are instilled on workers.

Cognitive and non-cognitive components of schooling: an elaboration

As already mentioned, Bowles et al. (2001) estimate that cognitive functioning explains between 16% and 18%[4] of the wage premium associated with schooling. Hence, they claim, human capital accounts for only a small portion of returns to education. Two observations are in order. First, Bowles et al. (2001: 1140) tend to restrict the notion of human capital to general cognitive ability. Second, the meta-analysis that supports their conclusion is based on rather poor measures of general cognitive ability. A substantial fraction (two fifths) of the cases of their meta-analysis is based, as they explicitly recognize (Bowles et al. 2001: 1151), on a very short and simple test that captures almost exclusively IQ.[5] However, skills relevant as human capital are obviously not restricted to IQ. It is not surprising, then, that they come to the conclusion that human capital does not matter much. If we define and measure human capital poorly, it will score poorly as a determinant of earnings.

We expand on the distinction in cognitive and non-cognitive components of schooling in three ways. First, we believe that a more elaborated notion of what counts as human capital is needed. In particular we need to distinguish between two components of cognitive skills. General cognitive ability (GCA) refers to information-processing skills that can increase the trainability and productivity of workers. These are

[4] It depends whether we consider the average or the median of their meta-analysis.
[5] Bowles et al. (2001: 1151-56) claim that results based on this simple measure (a short vocabulary test) are not substantially affected by measurement problems. They also re-run their models excluding cases based on this measure. Interestingly, to support their claim, they cite a study by Taber (1997) using a more detailed measure of general cognitive ability available for three time-points, and derive the following estimates of the cognitive component of schooling: 35%, 29% and 18% for 1982-84, 1985-87 and 1988-90 respectively. The first two estimates point to a substantially higher relevance of the cognitive component than suggested by Bowles et al. (2001). They are indeed rather close to the ones that will be presented in this paper. Bowles et al. (2001:1156) shortly comment also on a control analysis suggesting that using more comprehensive measures of general cognitive ability yields estimates about 10% larger than the narrower measures, another finding that is in accordance with ours.

general and abstract abilities that can be used in a wide range of domains, including the workplace. This is the component that Bowles and Gintis' cognitive measures try to capture, albeit rather imperfectly. However, precisely because of their general nature, they only represent a stock of skills that *potentially* can be developed and converted into job-relevant skills. Measures confined to GCA do not tell us if, and to what extent, this process of "human capital conversion" actually occurs. Individuals possess a wide array of reading, analytic, reasoning and communication skills, and they develop them to a different degree: some of these skills may be completely irrelevant for some jobs, and among the ones where they matter, some skills may matter more than others. If some workers have developed the "wrong" skills, measures of GCA alone will score poorly. This does not mean that human capital does not matter: it simply means that there is a skill mismatch. Then, we need to assess whether these cognitive skills are really relevant in the work domain. We want to know whether individuals possess *and use* the cognitive skills that are supposed to be relevant for their occupational performance. Therefore, information on GCA needs to be complemented with information on work-specific cognitive ability (WCA). This is the second analytic dimension of the notion of human capital that must be identified.

However, we suggest also that cognitive skills do not tell the whole human-capital story. There are some skills that are highly consequential for productivity, although they entertain weak connections with (general and work-specific) cognitive skills. The most evident case relates to manual work: several manual tasks involve abilities that can be quite sophisticated, while at the same time requiring few abstract cognitive skills. The productivity differential between a skilled and an unskilled manual worker can hardly be reduced to a cognitive ability differential. The widespread rhetoric on the “knowledge economy” should not obscure this simple observation: some occupational skills are weakly correlated with cognitive skills. This observation can be extended to many other segments of the workforce indeed. Just consider two accountants: one can use a software needed for his/her job, while the other cannot. We could reasonably claim that GCA is a useful resource to learn how to use the software, but once again who would reduce the productivity differential between the two accountants to a GCA differential? These observations point to the conclusion that there is a set of task-specific abilities which can be highly relevant for workers’ productivity, yet quite independent from cognitive skills. This is the third dimension of human capital that we define as Task-specific Manual Ability (TMA).

Due to data limitations, we cannot include measures of TMA, yet we believe that it is important to keep in mind the distinction between cognitive and non-cognitive components of human capital, if we are to avoid the mistake of equating “human capital” with (a poor measurement of) cognitive functioning. At the same time, our analysis is one of the few attempts to include a measurement for both general and work-specific cognitive skills (Carbonaro 2006, 2007). A second advancement of our study is that we control for selection processes in our empirical models, in order to be even more certain about the productive skills component of schooling. To do justice to the empirically grounded criticisms of human capital theory mentioned above, we need to control as much as possible for allocative processes that may “interfere” with the human capital interpretation of schooling. Therefore, we control for parental background (to control for allocation on the basis of cultural capital), occupational status (to control for credentialism), firm size and industry (to control for structural factors deviating from the human capital model). Certainly because our elaboration of the measurement of productive skills relies on survey questions asking the *usage* (rather than possession) of various types of cognitive skill, it is essential to control for allocative mechanisms that could affect the likelihood that some people use more cognitive skills than others, even if they possessed the same amount.

A third relevant extension is to examine cross-national variation in the cognitive and non-cognitive components of schooling. Bowles and Gintis' estimate of 82 to 84 percent of the education effect being non-cognitive is based on a meta-analysis of a large number of American empirical studies. It is likely that countries differ in the reasons why education pays off. In some countries, education may function more according to human capital theory with its strong emphasis on productive skills, than in other countries. Likewise, it is likely that countries differ in the extent to which education functions as a means to reward on the basis of non-cognitive qualities, for example in the form of credentialism, cultural capital, or structural location. Therefore, the value of social mechanisms explaining the education effect should be understood as conditional upon the structural-institutional setting in which employers and employees act.

Hypotheses

Above we have argued that productive skills affecting earnings are not limited to General Cognitive Ability (GCA), but include also work-specific cognitive ability (WCA) and Task-specific Manual Ability (TSA). This analytical distinction is relevant for the explanation of the education effect on earnings because these three dimensions are differentially distributed according to level and type of schooling. As for cognitive skills of a general nature, we have discussed in section 2 that different formulations of the neo-classical model attach a different importance to inherited ability and to the learning processes that take place at school, but they all view schooling as strictly associated to general cognitive skills that affect the productivity potential. It is a well-established empirical finding indeed that, even controlling for standard socio-demographic variables and information on occupational position, education and GCA covariate systematically (Farkas 1996; Oecd 2000). However, we expect that education affects also WCA. As far as students progress in the educational system, curricular specificity increases systematically. In some countries, such as Germany, educational specialization begins already in lower secondary education, in many others only the upper secondary level is differentiated into tracks or branches, while everywhere university education is organized in fields of study. This means that more educated people possess not only higher general cognitive skills but also *specialized* knowledge and cognitive skills that may be relevant for their future job tasks. For instance, a university graduate in economics has an ability to understand, analyze and use budgets, economic projections, etc. This leads to *hypothesis 1*: The more inclusive human capital skills are measured, i.e. including detailed indicators for both general and work-specific cognitive skills, the more strongly is the education effect reduced. [6]

Our distinction in different sorts of productive skills (general and work-specific) is an important start for studying cross-national variation. One important aspect in which countries vary, which has a large impact on the association between schooling and work, is the educational system. In particular the extent and nature of vocational

[6] Education is also likely to affect also highly specific productive skills with a weak cognitive component (i.e. TMA). This is particularly the case of vocational training: an extreme example is the German dual-system, with its hundreds of specialized courses (e.g. carpenter for iron industry). Several educational systems in continental Europe put a similar emphasis on such forms of specialized training for manual occupations. In the present paper we are not able to empirically disentangle this aspect of human capital, so we do not formulate hypotheses about it.

education is relevant here (Shavit & Müller 1998; Müller & Gangl 2003, and many others). A vocationally oriented schooling system is characterized by having multiple tracks within educational levels, some of which are vocationally specific, and others more generally or academically oriented. This means that graduates from different educational qualifications do not always vary in the amount of schooling, but will do in the type of schooling. This has an impact on both the cognitive endowments of school graduates and the relevance of schooling and cognitive skills on the labor market. In countries with less vocationally oriented schooling (such as the United States, and to a lesser extent the United Kingdom), educational qualifications are mainly indicative of the amount of general human capital school leavers have, whereas in vocationally oriented schooling systems (e.g. Germany, and to a lesser extent Netherlands) qualifications also signal the vocational relevance of skills. Therefore, in Germany and in the Netherlands the overall amount of schooling is less strictly associated to general cognitive skills. Indeed, previous studies (OECD 2000; Park and Kyiei 2007) indicate that these two countries exhibit considerably smaller associations between cognitive skills and schooling than the US and the UK. At the same time, if education in our two Anglo-Saxon countries is valued more as a device for screening on general cognitive skills, rather than for imparting strong vocational training, we should expect that this is because the importance of general cognitive skills for employers is particularly strong in the US and in the UK. Then, we can expect that the reduction of the education effect after controlling for general cognitive ability will be stronger in comparison to Germany and the Netherlands, because both the association between amount of schooling and GCA, as well as between the latter and earnings, is stronger (*hypothesis 2*). However, the reduction in the education effect after controlling for work-specific cognitive skills is expected to be relatively strong in Germany and the Netherlands, because employers reward education because of the work-specific skills that are acquired in school (*hypothesis 3a*). Relatedly, given the strong linkages between vocational school programmes and work places, it is expected that a wider range of work-specific skills is rewarded in Germany and the Netherlands than in the UK and the USA (*hypothesis 3b*).

However, it must be noted that an observed high reward of work-specific skills in Germany and the Netherlands could also be caused by country-variations in allocative processes. Due to the higher level of credentialization of access to occupations in Germany (Thelen 2004; Culpepper and Finegold 1999), German employers are far more restricted in the hiring process than their American and British counterparts. This will imply that allocative processes (on top of individual schooling and skill levels) will matter less for the explanation of the education effect through cognitive skills in countries where employers are more free to choose whom to hire (*hypothesis 4*). In other words, the comparatively large explanation of the education effect through work-specific cognitive skills in Germany is partly caused by the fact that allocative mechanisms (related to industry, occupational status, firm size and employment status) drive the relationship between education and the usage of work-related cognive skills more strongly in Germany than in the United States and Britain.

DATA, VARIABLES AND STATISTICAL MODELS

To test the magnitude of the productive skills component of schooling on the labor market in the UK, the USA, Germany and the Netherlands, we make use of the

International Adult Literacy Survey (IALS). IALS is a large-scale comparative survey realized under the auspices of OECD and coordinated by the Canadian statistical office that involved 21 industrialized countries between 1994 and 1998 (NCES 1998). Each country designed a sample that had to be representative of the civilian, non-institutionalized population aged 16-65. Although in some countries also older people were interviewed, the analyses reported here do not include them. No single sampling methodology was imposed to the participating national research teams, due to differences in the data sources available to them. For instance, Germany employed a three-stage sampling to select 4003 addresses (of which 997 did not belong to the target population). In each household one person was selected for interview using the Kish method. In the United Kingdom, two probability samples were selected: one for Great Britain and one for Northern Ireland. In the former a sample of addresses by postal code sectors was identified and for each of 35 addresses within each sector the Kish method was used to select one adult. In Northern Ireland a list of all private addresses was used to select a systematic sample of addresses from which one person per household was selected using the Kish method. In the United States a two-stage probability sample stratified by ethnicity and education was used. Also the Dutch team employed a two-stage sampling (postal codes were selected at the 1^{st} stage and addresses at the 2^{nd}). Response rates were respectively 69%, 63%, 60% and 45% for Germany, United Kingdom, the United States and the Netherlands[7]. Face-to-face interviews were conducted in homes in a neutral, non-pressuring manner. National questionnaires contained a large number of items that were submitted uniformly in all countries, but some items were optional and a free-component of items was permitted. Extensive

[7] When descriptive statistics are presented, they are based on weighted estimates to correct for sampling bias.

quality controls were conducted in order to ensure standardization and comparability of the core items across nations.

The main focus of the IALS survey is literacy, defined as “using printed and written information to function in society, to achieve one’s goals and to develop one’s knowledge and potential”. As can be seen, this is a wide-ranging definition that encompasses a broad set of information-processing skills that may be used at work, but also at home or with friends and acquaintances. That is why we will refer to this kind of ability as *general* cognitive skills. Three sub-dimensions of (general) literacy are identified in the IALS survey: prose, document and quantitative literacy, referring respectively to the capability to understand and use texts such as articles, stories, fiction (prose literacy), to identify and use information contained in various documents such as job applications or payroll forms (document literacy), and to mathematical skills to be mobilized when reading printed materials, for instance when completing an order form (quantitative literacy). For each of these three sub-dimensions five plausible values per respondent are available in the IALS data. The general procedure to obtain these 15 scores is known as Item Response Theory[8]. In our analyses we use the simple, standardized average of these 15 values. We have also run a factor analysis for these variables: in all countries under analysis, it invariably extracts one single factor that exhibits an almost perfect correlation with the simple mean that we will employ. This result is recurrent in studies based on the IALS data, as well as on similar datasets containing information on cognitive skills in different domains: it suggests that a one-dimensional representation of (general) cognitive skills is quite accurate (Devroye and

[8] Basically, this requires a pool of tasks of varying difficulty which assess the same underlying dimension. The scaling procedures first takes place on the basis of pre-test results and then, on the basis of the demonstrated performance, individuals can be assigned scores on the same scale. At the same time, it is possible to display the difficulty of each task in this scale. For an introductory explanation of this procedure, see NCES (1998). For details on the items submitted to respondents, see Oecd (2000).

Freeman 2001; Green 2001). At any rate, employing highly correlated measures for different skill domains would lead to severe multicollinearity problems.

Our measure of WCA is based on extensive texts of respondents´ cognitive abilities that comprise a total of 101 tasks, most of which are open-ended. Subsequent statistical analyses indicate that scoring of responses was implemented with a high degree of consistency across countries (NCES 1998). We believe that IALS data offer the unique possibility to measure GCA in the adult population in much greater detail and with higher methodological sophistication than it is usually possible (especially in large-scale comparative research).

We do not confine ourselves only to this measure, however. Our statistical models include also three measures of Work-specific cognitive abilities: respondents were asked how often they mobilized their cognitive skills at work in activities such as writing reports, reading budget tables, using foreign language texts, etc. (every day, a few times a week, once a week, less than once a week, rarely or never). Factor analysis was used to derive from 13 items three scales referring to different dimensions of WCA: linguistic skills, economic or financial skills and skills that are more typical of manual jobs. In appendix 1 we discuss in some detail the procedures used to derive our measures of WCA.

Schooling of respondents is expressed as the number of years of formal schooling completed by respondents (not counting repeated years at the same level). Parental schooling level is measured in three categories following the ISCED classification. We apply the dominance criterion that selects the highest school degree among the mother and the father. Each participating national team was responsible for coding national educational classifications into ISCED 1975. This has probably affected the degree of standardization of the coding (and ambiguities in the definition of categories 2 and 3 of ISCED 1975 may have further enhanced this problem). That is why we use an aggregated version of ISCED with only three categories for parental education (primary or lower secondary, upper secondary, tertiary education) and we restrict our measurement of respondents´ education to years of schooling, which is much less affected by these comparability issues.

Gross personal income from wages, salary or self-employment is not available as a cardinal variable in the IALS international data available to scientific users. Therefore, we are forced to employ an ordinal variable that locates respondent's income into one of the five quintiles of the national income distribution (for details, see NCES (1998)). There is obviously much important dispersion within each income quintile that cannot be captured by this measure. At the same time, we believe that using this ordinal variable is the best we can do to ensure a basic comparability between countries of our dependent variable. In order to control for working time, our models include a variable referring to the number of working hours per year. For some IALS countries, the standard variable of hourly wages employed in Mincer equations is available: control analyses indicate that results concerning both the importance of schooling and the role of cognitive skills are basically unaffected by the way income is measured (Harmon et al. 2003)[9].

[9] The income variable refers to yearly income, instead of monthly income, for all nations, except for Germany, which may lead to over-estimating income inequality in this country relative to the others (Devroye and Freeman 2001). If anything, this possible bias should work against our research hypotheses. Moreover, it should be noted that we cannot differentiate between Western and Eastern Germany. The educational system exhibits a less strong vocational emphasis in the latter case. Also this data limitation is expected to work against our hypotheses. Finally, it is worth mentioning that sources of income other than wages (e.g. interests, dividends, government subsidies) are not covered by our income measure, which probably results in an underestimation of overall economic returns to education. See Carbonaro (2006) for a detailed discussion of merits and limitations of the IALS measure of income.

Gender, age, parental education[10] and ethnicity are introduced as control variables. The squared term for age is also included. The covariate for ethnicity measures whether the respondent was born in the country of interview. As for age, it may be noted that in standard Mincer equations work experience is typically introduced as a component of human capital. Age or the number of years since the respondent left the school system are often used as (highly imperfect) proxies for accumulated experience. Adequate information on job experience is not available in the IALS data, hence we only fit the age covariate[11] as a control variable and avoid any substantive interpretation (which may refer both to cohort and life-cycle effects indeed).

As our conclusions remain unchanged no matter if we include or exclude self-employed and agricultural workers, we present results that include them in order to increase sample size and to rely on more robust estimates. We include only people aged 25 or older. We have also compared models with and without respondents aged between 16 and 24. If individuals in this age range are excluded, the estimates refer more directly to *final* educational achievement and earnings are less often measured in the initial stages of occupational careers. Excluding younger people results in a higher estimate of the influence of schooling on earnings.

As our dependent variable is not cardinal, we cannot use OLS regression. The IALS income variable assigns individuals to the appropriate quintile of the national wage distribution, thus creating five discrete income bands. Interval regression, a generalization of censored normal regression, represents the ideal solution in this context. This statistical technique assumes that the observed discrete response variable

[10]The information on parental occupation is lacking or incomplete for most IALS countries.
[11] One could use the information on respondent's age and years of schooling to compute indirectly a proxy for job experience, but fitting the three variables simultaneously would lead to a multi-collinearity bias, especially because sample size is not very big for some countries.

is derived from a continuous unobserved variable. Assumptions concerning the distributional properties of the unobserved variable and error terms are very similar to assumptions of standard OLS. It should be noted that our interval regression estimator produces more consistent estimates than OLS regression using mid-points of the wage bands (Stewart 1983). Moreover, this technique does not require the strong assumptions of ordinal logistic regression (i.e. the proportional odds assumption). Furthermore, it is a linear technique that allows for causal decomposition of the effects of covariates, just as in OLS-based path-analyses. This means that we can first estimate the total effect of education on earnings, controlling for a number of socio-demographic factors, and then examine to what extent this effect is "explained away" by our measures of GCA and of WCA.[12]

It will be noted that in our models we do not control for inherited ability and motivation, which can influence both educational achievement and earnings. Then, the estimate of the casual relationship between the two may be spurious, if these confounding factors are not neutralized. The solution to this problem has been a core issue in the economic literature on returns to investment in human capital over the past 30 years. The most frequent research strategies involve either fitting a large number of control variables that should reduce the above-mentioned spurious effects or opting for the instrumental variables approach. However, with the IALS data it is very difficult to deal with these issues. Moreover, the two proposed solutions have proved rather unsatisfactory (Heckmann et al. 2003) and it is fair to say that there is no consensus on

[12] We are mainly concerned with the relevance of cognitive skills as a *mediation variable* that could partly account for the effect of education on earnings. The independent contribution of cognitive skills to the overall *explained variance* in earnings equations is not considered in detail here. However, Bowles et al. (2001) raise also the issue that this contribution is negligible, according to their estimates. Hence, we present some information on this issue. It should be noted that, particularly in the case of ordinal regression, results on the explained variance of a given model are rather sensitive to the different fit-statistics employed. This is less the case, however, when considering *variations between models* of R2-type measures. Here we present results based on McKelvey and Zavoina's (1975) R^2.

the proper methodology to be adopted. However, economists tend to agree that some selection effects are at work, but they are of minor relevance relative to the importance of the investment in education (Card 1999; Green 2001; Heckman et al. 2003). Finally, it must be stressed that we are not interested in disentangling the “pure effect” of attending school from that of inherited ability. Instead, we want to estimate to what extent more educated people earn more because of higher productive skills, no matter if these are due to inherited ability and motivation to achieve, to schooling, or to a mix of these influences[13].

RESULTS

Our starting model estimates the total effect of education, controlling for socio-demographic variables. We can see from table 1 that in all countries education exerts a strong effect on earnings. For instance, in the United States one year of education ensures a wage return of 2,42 percentiles. This means that eight years of schooling “move up” an individual of almost one quintile in the income distribution (2,42*8=19,4). In accordance with other research, the wage returns to education are strongest in the United States, closely followed by the UK, while they appear considerably lower in Germany and in the Netherlands (Devroye and Freeman 2001; Harmon et al. 2003). This is in line with the previous observation that years of education is a poorer measurement of educational attainment in stratified educational

[13] We also recognize that unobserved heterogeneity may affect our comparisons between countries. For example, cross-national variations in employment rates imply a different selection into the labour market, and particularly in the case of women this may be related to education. Moreover, cross-national variations in the individual dispersion on unobserved skills may contribute to explaining the observed differences between nations. However, previous empirical analyses addressing these issues suggest that they are of limited relevance (Devroye & Freeman 2001; Blau and Kahn 2005).

systems (such as Germany and the Netherlands) than in countries with a more hierarchical system like the USA and to a lesser extent the United Kingdom (Leuven et al. 2004).

As for the other parameters reported in table 1, they refer to control variables, therefore we will not comment on them extensively. Suffice it to say that gender has the expected negative effect on earnings, also controlling for level of education and worktime. This latter variable has a predictable positive effect. Table 1 also indicates that work income increases with age at a decreasing rate and that parental education has a relatively weak, positive impact on income, at least in the US and in the Netherlands, once we control for respondents´ education. Finally, immigrant status has a negative impact on wages in all countries, except for the Netherlands, but this effect is significant only in the case of Germany.

[Table 1 about here]

Table 2 describes the results of two subsequent models for each country. The first one adds to the previous model the average score in the IALS literacy tests, i.e. our measure of general cognitive ability (GCA). The second model includes also the factor scores derived from the factor analysis on the degree of mobilization of skills at work, i.e. our measure of Work-specific cognitive abilities (WCA). Both kinds of measures are based on normalized variables. The overall configuration of parameters remains basically unchanged relative to the first model, so we will not comment on them in detail. The effects of family and ethnic background are rather small, while the effects of gender, age, age squared and worktime are significant and go in the same direction as before (except for the non-significant age effect in Germany).

Our relevant finding is that, if we compare the effect of education on earnings in tables 1 and 2, we can conclude that it is explained away to a relevant extent by our two measures of productive (cognitive) skills. Namely, fitting only our measure of GCA results in a reduction of the effect of education of 36.6% in the UK, of 34.4% in the US, of 24% in Germany, and of 33.4% in the Netherlands. These results are in accordance with previous literature based on IALS data, as well as on similar surveys (Murnane et al. 1995; Green 2001; Denny et al. 2004; Blau and Kahn 2005; Carbonaro 2006; but see Charette & Meng 1998). IALS literacy scales are particularly valuable for our purposes because they are not intended to measure merely IQ, abstract reasoning or any other ability specifically valued at school, rather they are explicitly designed to capture literacy skills *applicable* in daily life. Hence, it is not surprising that they display higher explanatory power than most of the cognitive measures employed by Bowles et al. (2001). [14]

[14] Previous literature has examined the possibility that economic returns to education and to general cognitive skills are not uniformly distributed in the population. Let us shortly comment on this issue, although it should be borne in mind that more robust results would require a bigger sample size. First, our analyses confirm previous findings that cognitive skills are particularly relevant for young workers; however the interaction effect between age and cognitive skills is not very strong, nor is it robust across countries. Second, we find that returns to education are higher for women in all countries under examination: although on average they earn less than men, they benefit more from the investment in education (*see* Denny et al. 2002; Harmon et al. 2003). However this is not the case for returns to cognitive skills, which display a similar importance for males and females. Third, we tested whether returns to formal schooling vary according to the level of cognitive skills: simply put, the idea is that the more people learn at school, the more they benefit from their school degrees. However, we found support for this hypothesis only for the US. Finally, it may be noted that, in line with previous studies, we find that including or excluding immigrants does not affect our results, except for the US where immigrants benefit more than natives from better cognitive scores (*see* Blau & Kahn 2005). The substantive interpretation of this finding is quite ambiguous, as we do not know whether it is cognitive ability or more simply linguistic competence what really makes the difference (Kerckhoff et al. 2001; Devroye&Freeman 2001). We have also experimented with quadratic or cubic terms for the effect of cognitive skills, which indeed turned to be well-described in linear terms, as reported also by Carbonaro (2006). Results are available upon request to the corresponding author.

Table 2 also indicates that GCA does not tell the whole human capital story. Indeed, if we add also the information on WCA, the reduction of the education effect amounts respectively to 62.8%, 50.8%, 53.1% and 63.1% for UK, US, Germany and the Netherlands. Hence, after adding indicators of these two dimensions of productive skills, the effect of schooling is at least halved (as in the United States) and at most reduced by around two thirds (as in the UK). Although it still remains significant, the education effect is now of moderate size in the UK and in the US, while it has become almost negligible in Germany and in the Netherlands. These reductions, representing the cognitive component of schooling, are much larger than reported by Bowles and Gintis. Thus, our support for the cognitive skills explanation of schooling is much stronger, albeit using different measures of cognitive abilities than Bowles and Gintis. Yet, a substantial fraction of the education effect remains unexplained by our extensive list of cognitive qualities.

Interestingly, the reduction of the education effect is attributable both to GCA and to WCA, with positive influence on earnings, be it to a different extent between countries. However, in the case of WCA, only linguistic and mathematic and financial skills display a significant effect, while our (rather poor) measure of manual skills seems rather irrelevant in all countries, except for the UK (see appendix 1).[15] Interestingly, WCA mediates to a significant extent the influence of GCA, particularly so in the UK and in the Netherlands.

In Table 3 the results are displayed of similar models as in tables 1 and 2, but now with an extensive control for selection and allocation variables that could affect the usage of cognitive qualities. These variables are organizational size, industry,

[15] Note that work specific *manual* skills, the third form of human capital that is theoretically relevant, is not empirically distinguishable in the data.

occupational status, supervisory status, and self-employment. They are needed to make sure that the differential reward of cognitive abilities across countries (and their impact on the reduction of the education effect) is not affected by country differences in the extent to which allocation processes lead to higher earnings (Carbonaro 2006). Although different rates of reduction of the education effect result from these models relative to table 2, the general pattern is rather similar. First, even after controlling extensively for selection processes, cognitive skills "explain out" a relevant portion of the education effect on earnings. When looking at general cognitive ability alone, our estimate is that the cognitive component of returns to schooling varies between 23 and 32 percent, depending on the country that is analyzed. If we extend the conceptualization of cognitive skills, the cognitive component of schooling rises to between 34 and 53 percent, depending on the country. This means that its influence is estimated to be at least twice as the estimate by Bowles et al. (2001), even after controlling for selection processes.

Second, the reduction of the education effect after only controlling for general cognitive ability is smallest in Germany, and of similar size in the other three countries. This supports at least partially hypothesis 2, which expected a stronger reduction in the USA and Britain. The Netherlands falls less evidently on the German side than expected, perhaps given the school-based orientation of vocational education (relative to the large dual apprenticeship system in Germany). Such a school-based system may induce employers more strongly to reward schooling on the basis of general cognitive skills than a country where the dual system allows more detailed understanding on the part of employers of the different skills and other traits available in their applicants and apprentices.

Looking at the rewarding of the work-specific cognitive skills, it appears that in Germany and the Netherlands a wider combination of work-relevant cognitive skills are rewarded than in the USA and the UK (like hypothesis 3b predicted). So in this regard the Netherlands and Germany are much alike; something one would expect on the basis of their vocational schooling system. Also, the reduction of the education effect in the model including general and work-specific skills relative to the model with only cognitive skills is strongest in Germany, indicating that including the work-specific skills are more strongly reducing the education effect than elsewhere.

In order to shed some light on the relative importance of the inclusion of general cognitive ability and work-specific cognitive abilities in the four countries, we can compare the percentage reduction of the education effect from the general cognitive skills model (models 2 and 5) versus the reduction from the extended cognitive skills model (models 3 and 6). The 'reduction ratio' of these reductions is preferred to solely examining the change in the main effect of years of education between the models, because the ratio neutralizes the problem that countries vary in the appropriateness of years of education as a measure of educational attainment (Leuven et al. 2004).

[Table 4 about here]

Table 4 shows these reduction ratios for the four countries for two sets of models separately (one without controls for allocative mechanisms as in table 2, and one with controls for allocative mechanisms as in table 3) .This reduction ratio is high in the Netherlands, where the reduction in the extended model is between 1.7 and 1.9 times the reduction of the general cognitive skills model (depending on whether we take the models from table 2 or 3). For example, the reduction in model 3 for the Netherlands (63.1 %) is 1.9 times the reduction of model 2 (33.4%). In Germany this reduction is 2.2 times as large in the model excluding allocation variables (table 2) and 1.5 in the model controlling for allocative processes (table 3). This large difference between the tables indicates that in Germany work-specific cognitive skills are to a larger extent rewarded *because of* allocative processes rather than pure productive skills, which was expected on the basis of relatively strong credentialization processes (hypothesis 4). The relative reduction factor for the US is 1.5 (table 2) and 1.2 (table 3), and for the UK 1.7 (table 2) and 1.5 (table 3). This indicates that the inclusion of work-specific cognitive skills is relatively important in the Netherlands and Germany (with the UK being very close); and much less important in the USA.

CONCLUSIONS AND DISCUSSION

In this paper we examined to what extent education is rewarded on the labor market through the mechanism of the cognitive skills it indicates; whether there are cross-national differences in this process, and how we can explain these cross-national differences. Following neo-classical economic theory as well as its sociological allies in modernization and meritocratization theories, we would expect cognitive skills be the main mechanism through which educational qualifications are rewarded. Contesting this assumption, Bowles and Gintis (2000; 2002; Bowles et al. 2001) argue that only a small fraction of the education effect on wages is cognitive. We used data from the International Adult Literacy Survey (IALS) for the United States, United Kingdom, Germany and the Netherlands to examine the size of the cognitive component of schooling. In order to give the cognitive explanation a fair chance, we extended the types of cognitive skills that are incorporated, and distinguished between general cognitive ability and three types of work-specific cognitive abilities (literacy, financial, manual). Our results indicated that a larger fraction of the education effect is cognitive than shown by Bowles and Gintis. When looking at general cognitive ability alone, our estimate is that the cognitive component varies between 23 and 32 percent, depending on the country that is analyzed. If we extend the conceptualization of cognitive skills, the cognitive component of schooling rises to between 34 and 53 percent, depending on the country.

Importantly, we showed that the relative importance of general versus work-specific cognitive abilities varies systematically between countries, with a larger fraction of the schooling effect being captured by the work-specific component in Germany and the Netherlands than in the US and the UK. This can be explained by the different role of schooling between countries. However, in many cases the UK and the Netherlands were less easily placed in the same corner as the US and Germany, respectively. Moreover, clearly the United States and Germany are contrasting countries with regard to the role of schooling on the labor market. In the United States the cognitive explanation for the impact of schooling on work outcomes is, with regard to *work-relevant* cognitive skills, rather weak. However, in Germany the *general* cognitive skills explanation fares poorly relative to the US. German employers reward schooling clearly not primarily for the general cognitive skill level it indicates, but rather use other criteria.

Independent of how we operationalize cognitive skills, it must be noted that a substantial fraction of the education effect remains unexplained and could thus be non-cognitive, calling for other explanations for the education effect, such as Bowles and Gintis´ model of incentive-enhancing preferences. To the extent that these are related to schooling, they could potentially explain part of the remainder of the schooling effect. However, it could very well be that these traits are productive, something that Bowles and Gintis are unclear about. On the one hand a productivity argument may be read in their statement that these traits are 'profitable to employers but are not the sort of "skills" that appear as arguments in a production function' (Bowles and Gintis 2000: 118). On the other hand, however, to the extent that incentive-enhancing preferences can be seen as 'rents' that distort market functioning, which is clearly the point taken in their study with Osborne (Bowles et al. 2001), these traits may be seen as non-productive.

A major limitation of our empirical analysis is that it only tests for human capital-based mechanisms, instead of evaluating *simultaneously* alternative hypotheses about the generation of earnings inequalities. Obviously, this limitation leaves room for the existence of alternative mechanisms - related to education, earnings *and* cognitive skills- that could reduce the explanatory power of cognitive skills. For instance, IALS data do not allow us to control for respondents´ cultural capital: we could only include parental education in three categories. More generally, the available information to control for selection processes was not optimal. Yet, it is worth mentioning that, in spite of these limitations, our structural variables referring to occupational position and location in the labor market exert a strong influence on earnings, even after controlling extensively for cognitive skills- a finding that may sheds light on the limitations of human capital theory.

Moreover, we should stress that our regression models indicate that cognitive abilities matter, but we still do not know to what extent they have a *direct* impact on productivity, or if they are important because they shape the capability to learn within organizations, or because they are related to innate abilities. So, we should carefully avoid any over-simplified interpretation that equates cognitive skills with (directly) productive skills. Quite to the contrary, our results seem to indicate some sort of complementarity between human capital and credentialist perspectives. On one hand, we have systematically found that: a) controlling for formal schooling (measured in years of education), work-specific skills influence earnings; b) work-specific skills mediate a relevant portion of the influence of *general* cognitive skills on earnings; findings that support human capital theory. On the other hand, it is still the case that: c) controlling for work-specific skills, formal schooling has an effect on earnings; d) the influence of general skills on earnings is never fully explained out by work-specific skills; indicating support for theories of credentialism and screening.

At the same time, it should be recognized that, although we improved considerably upon the standard measures of cognitive ability, there are many productive skills that could be thought of that lead to higher levels of productivity, which are not included in our models. For instance, our data did not contain information on skills acquired through on-the-job training or task-specific manual skills that may be weakly related to cognitive skills. We would hold these work-relevant skills as important individual skills in the true 'human capital' sense of the word. Future research should make an effort in measuring the diverse sets of education-based skills, just as it would be highly useful to disentangle the role of specific non-cognitive skills as determinants of earnings. We regard these two research developments as complementary. We would maintain, however, that the previous observations do not dismiss our crucial claims, namely that cognitive resources can be highly rewarding in the labor market, that they "explain out" a relevant portion of the effect of education on earnings and that their role is likely to vary across countries.

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Table 1: The relationship between schooling and earnings in UK, USA, Germany and the Netherlands

	United Kingdom	**USA**	**Germany**	**Netherlands**
	Model 1	*Model 1*	*Model 1*	*Model 1*
Gender (female)	-13.447	-9.707	-12.514	-13.535
	[11.16]**	[8.75]**	[7.64]**	[10.18]**
Age	2.220	2.105	0.289	2.160
	[5.20]**	[4.78]**	[0.44]	[4.40]**
Age squared	-0.026	-0.021	-0.001	-0.020
	[5.13]**	[4.12]**	[0.15]	[3.42]**
Immigrant status	-1.126	-2.377	-6.757	0.735
	[0.49]	[1.62]	[2.52]*	[0.31]
Parental education Upper secondary	-1.576	5.021	-1.909	1.937
	[0.72]	[3.79]**	[0.74]	[1.55]
Parental education Tertiary	0.512	5.051	-4.974	5.627
	[0.31]	[3.16]**	[1.61]	[3.68]**
Years of schooling	2.360	2.418	1.552	0.990
	[12.65]**	[13.56]**	[6.62]**	[8.18]**
Working hours	0.016	0.013	0.017	0.012
	[16.69]**	[12.49]**	[13.09]**	[11.36]**
McKelvey and Zavoina R^2	0.47	0.41	0.42	0.43
N	1788	1343	732	1489

Notes to the table:
Reference categories: gender: male; immigrant status: native; parental education: primary or lower secondary.
Robust z statistics in brackets * = significant at 5%; ** = significant at 1%

Table 2 The relationship between schooling, cognitive skills and earnings in UK, USA, Germany and the Netherlands

	United Kingdom		USA		Germany		Netherlands	
	Model 2	*Model 3*	*Model 2*	*Model 3*	*Model 2*	*Model 3*	*Model 2*	*Model 3*
Gender (female)	-12.113	-12.160	-10.332	-11.200	-12.214	-11.957	-13.896	-13.658
	[10.38]**	[11.09]**	[9.48]**	[9.95]**	[7.57]**	[7.46]**	[10.53]**	[10.77]**
Age	1.836	1.671	1.978	2.059	0.317	0.183	2.045	2.035
	[4.39]**	[4.22]**	[4.63]**	[4.91]**	[0.48]	[0.29]	[4.21]**	[4.40]**
Age squared	-0.020	-0.018	-0.019	-0.020	-0.001	0.001	-0.018	-0.018
	[4.14]**	[3.95]**	[3.90]**	[4.20]**	[0.11]	[0.08]	[3.07]**	[3.30]**
Immigrant status	1.972	1.337	2.561	3.606	-3.284	-1.236	2.904	2.412
	[0.90]	[0.66]	[1.65]	[2.38]*	[1.17]	[0.45]	[1.29]	[1.20]
Parental education upper secondary	-3.429	-3.027	2.253	1.870	-2.312	-3.449	1.101	-0.174
	[1.62]	[1.57]	[1.71]	[1.46]	[0.90]	[1.36]	[0.89]	[0.14]
Parental education tertiary	-1.390	-1.086	2.774	2.296	-6.170	-6.002	4.421	3.124
	[0.85]	[0.70]	[1.79]	[1.54]	[1.99]*	[1.95]	[2.90]**	[2.17]*
Years of schooling	1.496	0.877	1.585	1.189	1.180	0.728	0.659	0.365
	[7.60]**	[4.69]**	[7.66]**	[5.75]**	[4.83]**	[3.01]**	[5.17]**	[2.99]**
Working hours	0.015	0.013	0.012	0.011	0.017	0.015	0.012	0.010
	[17.15]**	[14.18]**	[11.64]**	[10.61]**	[13.47]**	[11.78]**	[11.10]**	[9.43]**
General cognitive skills	7.502	4.586	6.652	5.433	4.315	3.497	4.260	2.256
	[11.08]**	[6.89]**	[8.37]**	[6.56]**	[5.28]**	[4.42]**	[7.07]**	[3.65]**
Work-specific linguistic skills		8.426		5.355		5.612		5.947
		[15.59]**		[8.55]**		[7.67]**		[10.50]**
Work-specific financial skills		2.312		-0.023		2.462		2.422
		[5.00]**		[0.05]		[3.25]**		[4.72]**
Work-specific manual skills		1.503		0.309		0.551		0.326
		[3.29]**		[0.60]		[0.76]		[0.65]
McKelvey and Zavoina R^2	0.51	0.58	0.44	0.48	0.45	0.49	0.45	0.50
N	1788	1788	1343	1343	732	732	1489	1489
Reduction in education effect relative to model 1 (%)	36.6	62.8	34.4	50.8	24.0	53.1	33.4	63.1

Notes to the table:
Reference categories: gender: male; immigrant status: native; parental education:
primary or lower secondary. Robust z statistics in brackets * = significant at 5%; ** = significant at 1%

Table 3: The relationship between schooling, cognitive skills and earnings (controlling for selection processes) in UK, USA, Germany and the Netherlands.

Variable	**United Kingdom**			**USA**			**Germany**			**Netherlands**		
	Model 4	*Model 5*	*Model 6*	*Model 4*	*Model 5*	*Model 6*	*Model 4*	*Model 5*	*Model 6*	*Model 4*	*Model 5*	*Model 6*
Years of schooling	1.147	0.830	0.662	1.669	1.136	1.027	0.702	0.539	0.464	0.637	0.431	0.298
	[6.03]**	[4.27]**	[3.47]**	[8.77]**	[5.44]**	[4.90]**	[2.49]*	[1.88]	[1.58]	[4.95]**	[3.24]**	[2.35]*
General cognitive skills		3.874	3.170		5.125	4.735		2.499	2.325		3.253	2.135
		[5.61]**	[4.66]**		[6.38]**	[5.72]**		[3.21]**	[3.00]**		[5.33]**	[3.44]**
Work-specific linguistic skills			5.393			3.583			2.716			4.819
			[8.80]**			[5.55]**			[3.16]**			[7.57]**
Work-specific financial skills			0.649			-0.195			2.012			1.866
			[1.25]			[0.39]			[2.51]*			[3.31]**
Work-specific manual skills			0.791			-0.142			0.864			0.181
			[1.73]			[0.28]			[1.07]			[0.36]
McKelvey and Zavoina R^2	0.61	0.62	0.65	0.49	0.50	0.52	0.51	0.52	0.53	0.48	0.49	0.51
N	1509	1509	1509	1313	1313	1313	655	655	655	1487	1487	1487
% Reduction in education effect relative to model 4		27.6	42.3		31.9	38.5		23.2	33.9		32.3	53.2

Notes to the table:

Added controls: gender, immigrant status, parental education, age, age squared, working hours, sector (primary sector, secondary sector/industry, private service sector, public service sector); isco occupational group (1 digit); employment status (employee/self-employed); supervisory status (yes/no), firm size (see appendix 2).

Robust z statistics in brackets * = significant at 5%; ** = significant at 1%

Table 4: Reduction ratios in the education effect

	United Kingdom	**USA**	**Germany**	**Netherlands**
Models without allocative variables (Table 2)	1.7	1.5	2.2	1.9
Models with allocative variables (Table 3)	1.5	1.2	1.5	1.7

Note: The reduction ratio is calculated by the percentage reduction of the direct education effect in a model including both general cognive ability and work-specific abilities, relative to the percentage reduction in a model only including general cognitive ability. Thus, for example in the UK the reduction of the education effect in model 3 versus model 1 (table 2) is 1.7 times as high as the reduction in model 2 versus model 1 of table 2 (62.8 versus 36.6 percent).

APPENDIX 1: Measuring Work-specific Cognitive Ability

This appendix describes how the measures for work-specific cognitive ability (WCA) were derived. Respondents were asked how often they used their cognitive skills at work in order to accomplish a number of tasks. As can be seen from the table below, some items referred to reading tasks (R), some others to writing tasks (W), yet some others to tasks involving mathematical skills (M). For instance, the item “R articles, reports, magazines, journals” refers to the following question: “how often do you read reports, articles, magazines or journals as part of your main job?” (see Oecd (2000) for the exact wording of each item). The same items were submitted to all employed respondents of the four countries.

These 13 items were then submitted to factor analysis, with principal component analysis as extraction method, *eigenvalues* over 1 as extraction criterion and varimax rotation. The estimated scores for each underlying dimension are obtained via the regression method.

The results of factor analysis reported below point to considerable similarities between nations, which could be taken as tentative evidence that items were understood in a roughly similar way across countries. Also the total explained variance, which ranges from 56,1% to 60,2% is very similar across nations. In all four countries factor analysis extracts three dimensions and the factor loadings suggest a very similar interpretation of these dimensions for each country. Namely, the first component refers to linguistic skills (such as reading or writing reports), the second to mathematical and financial skills (such as reading or writing invoices and budget tables), while the third one refers to abilities and tasks that are typical of manual jobs (such as making estimates of the size or weight of objects). Bold characters in the table below facilitate the substantive interpretation of results by suggesting to which dimension(s) an item belongs.

A detailed comment of these results is outside the scope of this paper. However, three observations are in order. First, it is extremely difficult in a large-scale survey to collect information on the specialized knowledge and skills that are required in each specific occupation, as would require our notion of WCA. Hence, it is a forced choice to rely on indirect measures: for instance, if a worker often reads budget tables as part of her/his main job, we assume that this requires the possession of specific financial skills that make the accomplishment of this task possible, although we cannot measure the level of these skills in detail. This assumption could be viewed as problematic, and here we come to our second point.

These items do not refer to skills *per se*, but rather to the possession *and* mobilization of them. On one side, this represents an advantage: as noted by Bowles et al. (2001:1157), what matters for earnings is not only how people *can* perform, but also what they *actually* do. On the other side, by controlling for variables on occupational position in the analyses reported in the text, we ensure that our measures of WCA do not merely reflect the structural location of respondents´ occupations. In other words, after controlling extensively for occupational variables, we can assume that typical performance reflects skills endowments to a considerable extent. In other words, differential performance among workers in similar positions reflects skills differentials. Indeed, it can be shown with the IALS data that, controlling for occupational variables, workers performing less on the job give lower self-ratings of their cognitive skills and admit more often that skills shortages are limiting their job opportunities, in line with our interpretation.

Our third and final observation is that the substantive interpretation of the third factor dimension is not very clear-cut, also because of some variations between countries in the correspondent factor loadings. At the same time, it is fairly clear that this dimension refers to *cognitive* skills and tasks that are typical of *manual* jobs or, at any rate, of jobs located at the lower levels of the occupational hierarchy. It must be considered that the IALS questionnaire is intended to measure the degree of mobilization of cognitive skills for occupations of a different kind and with a varying degree of complexity, but it does not allow the measurement of the *non-cognitive* productive skills discussed in the theory section.

Table A1: Factor analysis of the IALS items on reading and writing at work

Great Britain	Components		
Items	Linguistic	Financial	Manual
R letters, memos	**,729**	,326	,057
R reports, articles, magazines, journals	**,780**	,231	,136
R reference books, catalogues	**,658**	,189	,364
R diagrams, schematics	,372	,049	**,671**
R invoices, budgets tables	,243	**,797**	,082
R foreign language materials	,281	-,092	,169
R instructions, directions	,226	,005	**,468**
W letters/memos	**,728**	,376	-,001
W invoices, budget tables	,262	**,725**	,052
W reports/articles	**,721**	,108	,180
W estimates/technical specifications	,223	***,454***	**,480**
M estimate size/weight of objects	-,113	,182	**,786**
M prices/budgets	,024	**,830**	,121
Total explained variance	**56,1%**		

Netherlands	Components		
Items	Linguistic	Financial	Manual
R letters/memos	**,736**	,356	-,042
R reports, articles, magazines, journals	**,765**	,175	,054
R reference books, catalogues	**,687**	,079	,252
R diagrams, schematics	**,583**	,129	**,435**
R invoices, budget tables	,312	**,773**	,109
R foreign language materials	**,572**	,120	,200
R instructions, directions	,404	-,197	***,323***
W letters/memos	**,707**	,379	-,148
W invoices, budgets	,079	**,804**	,093
W reports/articles	**,703**	,026	,053
W estimates/technical specifications	,306	,303	**,586**
M estimate size/weight of objects	-,056	,201	**,796**
M prices/budgets	,103	**,732**	,312
Total explained variance	**57,3%**		

United States	Components		
Items	Linguistic	Financial	Manual
R letters/memos	**,811**	,232	,102
R reports, articles, magazines, journals	**,811**	,189	,155
R reference books, catalogues	**,692**	,146	***,384***
R diagrams, schematics	,415	-,026	**,650**
R invoices, budget tables	,309	**,806**	,073
R foreign language materials	,094	,074	,115
R instructions, directions	,160	,124	**,451**
W letters/memos	**,783**	,304	,092
W invoices, budgets	,312	**,743**	,188
W reports/articles	**,675**	,206	,226
W estimates/technical specifications	,281	***,349***	**,591**
M estimate size/weight of objects	-,086	,085	**,806**
M prices/budgets	,109	**,787**	,190
Total explained variance	**60%**		

Germany	Components		
Items	Linguistic	Financial	Manual
R letters/memos	**,776**	,291	,088
R reports, articles, magazines, journals	**,819**	,159	,200
R reference books, catalogues	***,453***	,144	**,536**
R diagrams, schematics	,199	,034	**,768**
R invoices, budget tables	,228	**,790**	,191
R foreign language materials	,308	-,028	**,476**
R instructions, directions	,155	,190	**,379**
W letters/memos	**,765**	,333	,092
W invoices, budgets	,382	**,760**	,132
W reports/articles	**,673**	,134	,349
W estimates/technical specifications	,178	***,416***	**,612**
M estimate size/weight of objects	-,113	,227	**,761**
M prices/budgets	,141	**,836**	,177
Total explained variance	**60,2%**		

APPENDIX 2: The relationship between schooling, cognitive skills and earnings (controlling for selection processes) in UK, USA, Germany and the Netherlands.

Variable	GREAT BRITAIN			UNITED STATES			GERMANY			NETHERLANDS		
	Model 4	*Model 5*	*Model 6*	*Model 4*	*Model 5*	*Model 6*	*Model 4*	*Model 5*	*Model 6*	*Model 4*	*Model 5*	*Model 6*
Gender (female)	-13.540	-12.712	-12.015	-9.800	-10.028	-10.393	-12.651	-12.451	-11.976	-14.670	-14.669	-13.958
	[12.14]**	[11.44]**	[10.90]**	[8.78]**	[9.13]**	[9.22]**	[7.29]**	[7.20]**	[6.79]**	[11.01]**	[11.07]**	[10.76]**
Age	1.921	1.763	1.730	1.964	1.829	1.894	-0.196	-0.128	-0.111	1.915	1.827	1.874
	[4.70]**	[4.36]**	[4.35]**	[4.74]**	[4.50]**	[4.62]**	[0.30]	[0.20]	[0.17]	[4.06]**	[3.88]**	[4.09]**
Age squared	-0.022	-0.019	-0.019	-0.019	-0.017	-0.018	0.005	0.004	0.004	-0.018	-0.016	-0.017
	[4.50]**	[4.03]**	[3.96]**	[4.07]**	[3.77]**	[3.90]**	[0.60]	[0.55]	[0.51]	[3.18]**	[2.86]**	[3.03]**
Immigrant status	-1.357	0.016	-0.341	-1.018	2.541	3.460	-1.711	-0.125	0.610	1.393	2.952	2.470
	[0.61]	[0.01]	[0.16]	[0.75]	[1.72]	[2.37]*	[0.62]	[0.05]	[0.22]	[0.61]	[1.36]	[1.24]
Parental educ.= upper secondary	-2.331	-2.922	-2.756	3.714	1.747	1.482	-2.385	-2.560	-3.503	0.749	0.269	-0.411
	[1.16]	[1.48]	[1.40]	[2.93]**	[1.37]	[1.18]	[0.90]	[0.97]	[1.33]	[0.62]	[0.22]	[0.35]
Parental educ.= tertiary	1.991	1.206	1.404	4.753	3.233	2.844	-5.741	-6.087	-5.601	4.516	3.782	3.093
	[1.28]	[0.78]	[0.92]	[3.18]**	[2.20]*	[1.96]*	[2.03]*	[2.13]*	[1.92]	[3.06]**	[2.57]*	[2.17]*
Years of schooling	1.147	0.830	0.662	1.669	1.136	1.027	0.702	0.539	0.464	0.637	0.431	0.298
	[6.03]**	[4.27]**	[3.47]**	[8.77]**	[5.44]**	[4.90]**	[2.49]*	[1.88]	[1.58]	[4.95]**	[3.24]**	[2.35]*
Working hours	0.015	0.015	0.013	0.011	0.011	0.010	0.015	0.015	0.014	0.011	0.011	0.010
	[16.07]**	[16.56]**	[14.90]**	[11.66]**	[11.16]**	[10.49]**	[10.96]**	[11.39]**	[10.31]**	[10.31]**	[10.24]**	[9.39]**
General cognitive skills		3.874	3.170		5.125	4.735		2.499	2.325		3.253	2.135
		[5.61]**	[4.66]**		[6.38]**	[5.72]**		[3.21]**	[3.00]**		[5.33]**	[3.44]**
Sector= agric.	-3.278	-3.277	-3.077	-10.131	-10.253	-9.329	-12.319	-12.433	-10.069	-8.494	-8.041	-6.329
	[0.96]	[1.01]	[1.00]	[2.62]**	[2.65]**	[2.56]*	[2.11]*	[2.16]*	[1.69]	[2.74]**	[2.63]**	[2.16]*
Sector= private	-5.600	-5.264	-4.893	-6.137	-6.055	-6.281	-0.796	-0.728	-0.017	-0.248	-0.459	-0.649

tertiary												
	[4.58]**	[4.34]**	[4.06]**	[4.41]**	[4.43]**	[4.56]**	[0.41]	[0.38]	[0.01]	[0.19]	[0.36]	[0.51]
Sector=public service	-3.329	-3.094	-4.178	-6.674	-5.995	-6.721	1.026	1.002	1.456	-0.735	-0.770	-0.879
	[2.66]**	[2.49]*	[3.38]**	[4.65]**	[4.22]**	[4.71]**	[0.51]	[0.50]	[0.71]	[0.54]	[0.57]	[0.64]
Isco one-digit	2.719	2.341	1.647	1.679	1.270	0.895	1.984	1.775	1.282	1.765	1.466	0.754
	[11.45]**	[9.58]**	[6.33]**	[5.95]**	[4.39]**	[2.99]**	[4.35]**	[3.92]**	[2.66]**	[6.87]**	[5.56]**	[2.69]**
Employment status: self-empl	11.143	9.158	11.681	1.016	0.530	1.572	-2.417	-2.426	-2.515	-5.988	-5.914	-4.638
	[1.49]	[1.21]	[1.65]	[0.41]	[0.21]	[0.64]	[0.81]	[0.82]	[0.87]	[3.41]**	[3.43]**	[2.75]**
Supervisory status: yes	6.653	6.255	5.349	6.568	6.562	5.811	8.854	8.031	6.885	5.818	5.999	4.192
	[5.83]**	[5.56]**	[4.83]**	[5.90]**	[5.95]**	[5.23]**	[4.35]**	[3.95]**	[3.32]**	[5.15]**	[5.41]**	[3.78]**
Firm Size	0.010	0.009	0.007	0.015	0.014	0.012	0.014	0.014	0.013		-	-
	[5.32]**	[5.01]**	[3.83]**	[6.94]**	[6.96]**	[5.67]**	[4.60]**	[4.52]**	[4.35]**		-	-
Work-specific linguistic skills			5.393			3.583			2.716			4.819
			[8.80]**			[5.55]**			[3.16]**			[7.57]**
Work-specific financial skills			0.649			-0.195			2.012			1.866
			[1.25]			[0.39]			[2.51]*			[3.31]**
Work-specific manual skills			0.791			-0.142			0.864	-8.799	-5.949	0.181
			[1.73]			[0.28]			[1.07]	[0.36]	[0.57]	[0.36]
Observations	1509	1509	1509	1313	1313	1313	655	655	655	1487	1487	1487

Reference categories: gender: male; immigrant status: native; parental education: primary or lower secondary; sector=industry; employment status= Employee; supervisory status=no.