EDUCATION, EARNINGS AND SKILLS: A MULTI-COUNTRY COMPARISON

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Abstract:

This paper uses the measures of basic skills (or functional literacy) in the International Adult Literacy Survey to examine the impact of education and basic skills on earnings across a large number of countries. We show that the estimated return to formal education is sensitive to the inclusion of these measures: excluding them biases the return to education upwards in many countries to a significant degree, usually 1 or 2 percentage points. In almost all countries, the test scores have a well-determined effect on earnings although there is considerable variation in the size of the effect. The highest returns to skills tend to be in English speaking countries. Comparing results across countries, the returns to education and the returns to basic skills are not correlated. The evidence suggests that there is considerable benefit in many countries for policy intervention to increase the skill levels of workers. This should not just be directed at dealing with low-skilled individuals – there are gains across the skills distribution.

* Material from the International Adult Literacy Survey is used with permission of Statistics Canada who bear no responsibility for the calculations contained herein or for any interpretation made by the authors. This work forms part of the Policy Evaluation programme of the Institute for the Study of Social Change at University College Dublin with which the authors are affiliated. The financial support of Atlantic Philanthropies is acknowledged. Harmon acknowledges the award of the Nuffield Foundation New Career Development Fellowship at University College London. Corresponding author: Dr. Kevin Denny, Institute for the Study of Social Change, University College Dublin, Belfield, Dublin 4, Ireland. Phone (+353 1) 716 4613. Fax (+353 1) 716 1108, kevin.denny@ucd.ie

1. Introduction

Over the 1990's there has been a sustained and sizeable increase in the return earned by college graduates relative to the less educated, thus contributing to increased inequality. One explanation for this is that increased globalisation of markets has put downward pressure on the wages of low-skilled workers because of competition with low-wage economies. An alternative view is that changes in the workplace, particularly in relation to information technology, have put a premium on the skills required to make best use of that technology. This is referred to as "capital, skilled-labour complementarity". Distinguishing between these two explanations is important but difficult (and beyond the remit of this paper) but it is clearly imperative to know what the returns to skills are if policy makers are to make the correct decisions about the provision of training[1].

To avoid confusion, the term "ability" should be understood to mean innate ability whilst the term "skills" refers to acquired skills. However in much of the economic literature on skills, "skill" is actually *defined* according to the highest education level completed and not by any direct measure of skill. This is partly due to the lack of suitable data, especially outside the United States. Moreover while there is a body of work that examines the impact of measures of what one might call innate ability (of a cognitive nature, such as IQ scores) on outcomes (such as earning) this literature is not directly estimating the effect of acquired skills on outcomes. See Herrnstein and Murray's *The Bell Curve* (1994) for an extensive (and controversial) discussion of the ability/outcomes issue.

This paper examines the effect of skills on individual earnings using the International Adult Literacy Survey (IALS). This data contains measures of skills in several domains which are variously described as functional literacy or basic skills. We look at how the inclusion of such a measure of skills impacts upon the return to schooling. The multi-country

[1] Krussell, Ohanian, Rios-Rull and Violante (2000) suggest that capital-skill complementarity can explain much of the variation although Denny, Harmon and Lydon (2002) find evidence to the contrary

nature of the dataset allows for a comparative dimension to our analysis, existing papers on IALS have looked at either individual countries or a very small number of countries. We think there is value in looking at all available countries since they cover a wide spectrum of labour markets.

In the next section we provide an overview of the relevant literature on the effect of education and skills on earnings. Section 3 describes the IALS data and how we use it to model earnings. Section 4 contains the empirical analysis while section 5 concludes.

2. Modelling the effect of education and functional literacy on earnings

There is an enormous econometric literature estimating the impact of education on earnings. Studies based on the standard Mincer log-linear earnings equations typically show that the returns to education are around 6% to 8% per school year for men[3]. Blundell *et al* (2003) uses detailed education and later earnings information on a cohort of male individuals born in 1958 to estimate that the returns to a degree (typically of 3-year duration) relative to graduating from high school at 18 (with 2 "A level" qualifications – a necessary but not sufficient condition for admission to university) is a 24% wage premium.

An extension to the core model is to consider the role of an individual's innate ability on earnings while preserving the basic idea of the Mincer model of schooling as an investment. This is typically achieved by the inclusion of some measure such as an IQ score or a measure such as those recorded in surveys like the IALS or National Adult Literacy Survey (NALS). However it is unclear what is being actually measured in this extension. The researcher may be unable to distinguish between innate abilities (such as intelligence) and acquired skills such as literacy. This is highlighted by the use of terms such as "cognitive

[3] See Harmon, Oosterbeek and Walker (2003) and Heckman, Lochner & Todd (2003) for recent overviews of this literature.

skills" by Pryor and Schaeffer's (1999) study based on the NALS data, reflecting the somewhat ambiguous position of these measurements.

In this paper ability is defined as being that which one is born (and which is presumably stable over time). On the other hand basic skills are defined as something that can be acquired through education and training. We believe that functional literacy as measured in IALS corresponds to these skills. For a measure to be considered as innate ability, assessment should be carried out early in the life of the individuals before educational and other interventions. Furthermore the IALS was not explicitly designed to measure I.Q. or innate ability. Therefore, we will use the terms functional literacy or basic skills interchangeably to mean that which is measured by the IALS tests. However we do recognise that measures of skills such as those used in this paper clearly will reflect, to some extent, the innate ability of an individual, in that "smart" people are likely to find it easier to acquire additional skills or may better appreciate the benefits of it. Crucially the IALS measures should not be interpreted as a general measure of intelligence.

The previous literature, including those studies which sought to explicitly model ability rather than skills, are useful in motivating the model used in this paper. Firstly, from a technical point of view, they provide a useful exposition of omitted variable bias. Secondly, in the case of those studies which sought to estimate the effect of ability explicitly, the IALS measure (and skills generally) are likely to be highly correlated with these ability proxies. Griliches (1977) introduces ability explicitly into the derivation of the log-linear earnings function which has two effects on the basic calculus. More able individuals may be able to 'convert' schooling into human capital more efficiently than the less able. One might think of this as considering inherent ability and education as complementary factors in producing human capital so that, for a given increment to schooling, a larger endowment of ability generates more human capital. On the other hand, the more able may have higher opportunity costs since they will typically have greater earnings potential. If ability to progress in school is positively correlated with the ability to earn, this reduces the rate of return to schooling.

Empirically, least squares estimation requires that the explanatory variables are uncorrelated with the unobserved disturbance term in the equation. Where schooling and ability are correlated, if an individual's ability or motivation affects earnings but is omitted from the earnings equation the estimated return to schooling will be biased. The extent of the bias will be determined by the correlation between education and ability. If these two are orthogonal then even if ability is excluded there will be no omitted variable bias. This is unlikely to be the case in practice. The approaches adopted to deal with this issue typically include explicit measures for ability to proxy for unobserved ability such as IQ and other such tests[4]. The results of these studies have largely found favour with the notion of upward bias in least squares results. Blackburn and Neumark (1993) using US panel data find the OLS estimates to be some 30-40% higher when ability measures are excluded. Blundell, Dearden and Sianesi (2003) find evidence of an upward bias of around 30% in the returns to schooling if "ability" is ignored.

Boissiere, Knight and Sabot (1985) find that the return to education drops by two-thirds, once cognitive skills such as literacy are taken into account. In addition they find that this result holds albeit on a smaller scale for manual and non-manual workers, suggesting that proficiency in literacy is essential for productivity in all job markets. Cawley, Conneely, Heckman and Vytlacil (1996) find that a measure of general intelligence calculated using Principal Components does not significantly reduce the variance associated with wage regressions and the return to cognitive achievement is low relative to the return to education, experience and family background. They also find that the choice of occupation is determined by factors other than cognitive skills.

[4] There is, of course, a huge scholarly debate about whether IQ and other such test really do measure innate ability or whether they are culturally, racially or otherwise biased. See Fischer, Hout, Jankowski, Lucas, Swidler, & Voss (1996) for some discussion of this.

As previously stated, we consider that IALS literacy measures as being skills, which are acquired by the individual but are correlated with innate ability. Thus both the return to ability and the returns to skills suffer from the standard unobserved (innate) ability bias. However it should be noted that the inclusion of conventional measures of "innate ability" would *also* result in omitted variable bias. For example the British National Child Development (NCDS), has measures of certain abilities, mathematics at age 7 and a wider range at age 11. However it would be naïve to think that these are, in some sense, pure measures of innate ability. They are not devoid of contamination from environmental factors since children are exposed to quite different environments even in the first seven years and we know that children learn a lot in that period. For example McManus & Mascie-Taylor(1983) quantify some of the influences, including family background, on these measures. Thus it is difficult to envisage a situation whereby the omitted variable bias is eliminated completely. Note that much contemporary thinking in educational psychology emphasises the importance of "multiple intelligences" (e.g. Gardner, 1993) some of which are very unlikely to be reflected in conventional ability tests[1].

The decision of whether to use years of schooling or highest level of education completed is partly a matter of interpretation and to some extent a matter of taste. In the conventional human capital model additional years in education add extra human capital so years of schooling is the appropriate variable. With either a signaling or credentialist model it makes sense to include measures of the highest level of education completed.

In practice it is often difficult to distinguish between such approaches empirically and the present paper makes no attempt to do so, and frequently the implied rates of return from the two approaches give similar results (where, for example the return to a primary degree is

[1] Even the use of identical twins does not get avoid these problems since the correlation of IQ scores between identical twins, though higher than fraternal twins, is less than 1: .85 and .60 respectively being representative estimates.

often worth about three of four years worth of education)[5]. Moreover using years of schooling facilitates comparisons with the extensive international literature on the subject.

The basic Mincer model to be estimated is therefore

$$\ln y = \beta_0 + \beta_S S + \beta_X X + e \qquad (1)$$

The dependent variable is the natural logarithm of earnings, S is years of schooling and X is a set of control variables including a quadratic in age to allow for the concavity of wages with respect to experience. The estimated β's can then be interpreted as, approximately, the proportionate effect on earnings of a one-unit change in the corresponding variable. Our second specification augments (1) by adding the IALS measure of skills, denoted A, as discussed in the next section:

$$\ln y = \beta_0 + \beta_{S'} S + \beta_A A + \beta_X X + e \qquad (2)$$

The return to schooling when controlling for skills is denoted $\beta_{S'}$. In some cases we estimate a variant of (2) where the skills measure is normalised within each country to have a mean of zero and a standard deviation of one with a corresponding parameter of β_{AN}. This will not change the estimated value of $\beta_{S'}$.

3. The IALS Data Set and the Skills/Literacy Measure

The International Adult Literacy Survey (IALS) was carried out under the auspices of the OECD. In total there were 3 waves: 1994, 1996 and 1998[6]. The purpose of the survey was to measure the literacy level of the adult population and to provide a common mechanism that would allow comparison of literacy proficiency across countries rather than a mere count of the number of 'illiterate' people in the population. However it is clear from the study design

[5] See Krueger and Lindahl (1999) for evidence in favour of the linear-in-schooling model. Denny and Harmon (2001) use the IALS data and find evidence of "sheepskin" effects.

[6] The countries involved in the first two waves were Australia, Canada, Belgium, Germany, Ireland, Netherlands, New Zealand, Sweden, Switzerland, Great Britain, Northern Ireland, United States and Poland. The two main language groups in Switzerland and Canada were collected separately. Belgium refers to Flanders only. The final wave added Chile, the Czech Republic, Denmark, Finland, Hungary, Italy, Norway, Slovenia as well as the Italian speaking Swiss.

that the definition of literacy was not intended to be focused solely on comprehension, rather is was aimed at encompassing a broad range of skills used in the context of working, schooling and home duties which are much more cognitive in nature than the term 'literacy' at first suggests (OECD & HRDC, 1997). In other work it has been shown how performance on the test can be predicted by educational attainment (Denny, Harmon, McMahon & Redmond (1999)).

The level of functional literacy is measured on three scales: prose, document and quantitative. Prose literacy is the knowledge required to understand and use information from texts, such as newspapers, pamphlets and magazines. Document literacy is the knowledge and skill needed to use information from specific formats, for example from maps, timetables and payroll forms. Quantitative literacy is defined as the ability to use mathematical operations, such as in calculating a tip or compound interest. In order to provide an actual measure of literacy each individual was given a score for each task, which varied depending on the difficulty of the assignment. Scores for each scale ranges from 0-500.

Our measure of functional literacy is simply the average over the three types of literacy: prose, document and quantitative using the continuous measures of each. An alternative would be to use principal components e.g. to extract the first component from all 15 plausible values and use this as a measure. This gives virtually identical results since the weights within the component are almost the same; the correlation between the average over all 15 and the first component is about .98. Given the richness of the data one obvious question is whether one can fully exploit the information and measure the separate effects of the three types of functional literacy. Including the three separately never gives sensible conclusions: we think this because of the high correlation between them so we use the average over all three. This raises a deeper question of whether there are three dimensions to functional literacy and if there are whether the tests distinguish between them. This issue is not pursued further here but we note Reder’s (1998) analysis of the NALS casts doubt on whether those tests identified distinct types of functional literacy. This is also consistent with the results for Canadian IALS in Green and Riddell (2003).

IALS provides us with a unique opportunity to analyse the issue of the labour market impact of both schooling and skills in a comparative context. However estimation of earnings functions for the IALS data is complicated as the income data for most countries is only observed to fall in a certain interval on a continuous scale. IALS wage data is constructed on the basis of assigning individuals to the appropriate quintile of the wage distribution, providing a 5-category banded income variable. Stewart (1983) shows that better estimates are available by exploiting a distributional assumption for the continuous but unobserved variable with a maximum likelihood estimator than *ad hoc* procedures such as using the mid-points of the wage bands.

In this framework the unobserved continuous wage data is mapped into the discrete observed income bands. Some observations are left-censored - we know that the unobserved income is less than or equal to an observed censoring value. Similarly some observations are right censored - the unobserved income is less than or equal to an observed censoring value. The estimator is a natural generalisation of estimation of the censored normal which is in turn a generalisation of the well known Tobit estimator. For the 1998 wave of countries the data includes continuous measure of (annual) wages as well as the banded data. For consistency we use the banded data. If we use the continuous data for these countries the results are very similar.

Note that our earnings data specifies which of five bands the individuals *annual* labour market earnings are. The top category is unbounded. Using data on hours worked per year (which varies across individuals and is measured continuously) we can estimate a model for hourly earnings, where effectively the bands will vary across individuals. Estimation proceeds under the assumption that earnings are log-normally distributed which is generally found to be a reasonable assumption (with the possible exception of the upper tail which might be better characterised by a Pareto distribution). We also calculate robust asymptotic standard errors using the well-known method associated *inter alia* with Huber and White (see Gould and Sribney (1999) for details of estimation and computation).

Aside from the complications due to the estimation of a model with a banded dependent variable, the model is relatively standard. Our estimates are based on a standard linear earnings function where the earnings is expressed as a function of age and its square, dummy (binary) variables reflecting immigrant status, whether an individual lives in an urban or rural area and the sex of the individual and the variables of interest years of schooling completed and a single measure of skills/functional literacy.

Individuals' scores on these tests are likely to depend on a whole host of variables some of which are observed (like quantity of schooling, age, sex) and some are not (at least in this dataset) like intelligence or school quality. We do not attempt to model this latter relationship separately 'though it would be very interesting to do so. This is because we lack some of the crucial inputs into such a relationship and because to model earnings and ability simultaneously requires exclusion restrictions i.e. there needs to be variables that go in each equation but not in the other. We don't think there are such plausible exclusion restrictions for these countries in general. Exclusion restrictions are inherently not testable and require *a priori* reasoning[7].

Hence we take skills as a given when we estimate the return to it and to schooling. But since we know that schooling is likely to be an important input into the acquisition of skills it may be useful to think there being a "direct return" to schooling conditional on skills, and a

[7] See Hansen, Heckman and Mullen (2003) for an attempt to calculate the effect of schooling and innate ability on test scores. Ishikawa and Ryan (2002) consider the impact of schooling on literacy test scores using NALS data, Charette and Meng (1998) perform a similar exercise with Canadian data

"total return" which would also take into account the additional impact through skills acquisition. We estimate the former here, which is clearly less than the latter. The return to education when not controlling is not the same as the total return unless the schooling and literacy system is recursive (for further discussion, see Hansen, Heckman & Mullen, 2003).

4. The results

Table 1 shows standard descriptive statistics for the full sample and the sample used in the econometric analysis[8]. They show that for the most parts the sample used in the analysis is very similar to the overall sample. The proportion in rural areas (defined in IALS as living in a community with a population of 20,000 or less) is about 1% less in the full sample. The biggest difference is the proportion of young (16-25 years) people in the working sample, which is significantly lower than the overall sample largely because many of them are continuing in education.

[TABLE 1 HERE]

The estimates of the return to education from these simple earnings equations are presented in Figure 1 and Table 2. Here we summarise the earnings returns from education from our basic specification both excluding and including our skills measure. The data presented in Figure 1 is sorted in ascending order of the *differences* in the return from including skills, that is the vertical gap between each country's bars. The returns for a number of countries are not well known but in many respects are consistent with more general cross-country findings including those in the meta-study in Denny, Harmon and Lydon (2002). For

[8] We have not analysed the Australian data since the public use sample provided to us excludes it. Poland is excluded, as we were unable to discover the values defining the wage bands. The Italian-speaking sample for Switzerland is also omitted since the population is numerically small. All data analysis uses the weights provided to allow for under/over sampling though we find that this makes little difference.

example less developed or transition economies tend to have higher returns to education and this is borne out in Figure 1.

[INSERT FIGURE 1]

However what appears to be the most interesting aspect of this figure is the quite dramatic drop in the return when skills are included in some countries and that in particular the countries at the bottom end of the scale where the impact of including skills are low or insignificant are largely non-English speaking countries. That the return to schooling falls with the inclusion of skills reflects the fact those with education and skills will in general be positively correlated[9]. Of the five countries where the gap is greatest, four are English speaking. From the standard formula for omitted variable bias, this suggest that in these countries either the correlation between schooling and literacy is strong or the return to literacy is strong or some combination of the two.

[INSERT TABLE 2]

The alternative issue is to focus on the return to skills in these countries. To make the coefficient of this comparable across countries we also normalise the skill-level score to have mean zero and a standard deviation of one. Figure 2 presents the earnings return to this normalised measure of skills together with the return to schooling, sorted from lowest to highest returns to skills. These are the columns denoted β_{AN} and $\beta_{S'}$ respectively in Table 2. Note that the two variables are measured in different units since schooling is measured in years. The countries where the return to skills is highest are mostly English speaking countries, Ireland, Northern Ireland and USA. Surprisingly the return to skills is not

[9] The upward bias should not be assumed however: Charette and Meng (1998) use the Canadian Survey of Literacy Skills used in Daily Activities and find that including measures of literacy *increases* the return to schooling for females (and decreases it for males).

statistically significant in either of the Canadian sub-populations. It isn't obvious why Canada is such an exception. The sizes of the coefficients are in line with those in other countries but the estimated standard errors are much larger. Green and Riddell (2003) do not find that IALS skills measure is statistically significant but this is in a quite different specification with a number of interactions not considered here.

[INSERT FIGURE 2]

The range of returns is also quite large: at the top end of the scale a one standard deviation difference in skills is associated with almost a 20% wage premium whereas as the low end the premium is around 5%. This is greater variation than one typically finds in schooling returns. For example the standard deviation of β_{AN} is 10% whereas for β_{S}, it is only 6%. The correlation across countries between the two sets of returns is very low (just over 4%). This may be counter-intuitive. If one thinks of some economies being more "knowledge intensive" one might expect the returns to be positively correlated. That they are not suggests that these two measures of human capital are really picking up quite different sets of skills and provides a further argument for augmenting earnings equations with measures of skills such as are used here[2].

As an alternative way to present the results Figure 3 shows the earnings return from moving from the 25th to the 50th percentile (or median) of the distribution in terms of the equivalent number of years of schooling – in other words we illustrate how many years of schooling is required to equate the earnings return of a move from the 25th to 50th percentile in the test score distribution. This numeraire must ignore the effect of schooling on ability since we cannot estimate this term due to a lack of exclusion restrictions for every country in

[22] Note that the change in scores necessary to move an individual by one standard deviation will differ from country to country since the distributions differ not just in the means but in variances (and other moments).

the dataset. The results represent an upper bound of the number of years of schooling equating in terms of earnings to the move along the ability distribution.

[FIGURE 3 HERE]

This graph depends essentially on the relative size of the return to schooling and skills as well as the spread of scores. In the Netherlands moving from the 25th percentile of the skills distribution to the median is worth the equivalent of around 2.5 years of education[10]. Countries to the right on the diagram are where adult education which increases basic skills have the highest pay-off. To put it another way, if an individual in the Netherlands misses out on formal education early in life the prospects for increasing their earnings later on through acquiring basic skills are good. By contrast in Slovenia, Germany or Hungary the prospects are much worse since, particularly in Slovenia, the returns to schooling are especially high.

The preceding discussion is largely based on an assumption of linearity in scores in terms of the impact on earnings. Extending the policy implication outlined above might query whether policy should be directed at individuals with very low levels of functional literacy or be directed across the distribution of literacy scores. To address this we allow for non-linearity in the impact of literacy on earnings by using dummy variables for each quintile of the IALS score distribution instead of the literacy score itself.

The results, summarised in Figure 4, are interesting and somewhat surprising. The height of the first bar in each chart gives the return in moving the first to the second quintile, i.e. from being between 20% and 40% relative to the bottom 20% of functional literacy. In some countries such as Germany, Hungary or English speaking Canada the return to this first "leap" is negligible, co-incidentally these are countries in which the "linear" return is quite low. The biggest return to getting out of the bottom 20% is the United States where it translated to around a 30% wage increase. What is interesting to see is that different quintiles

[10] The same picture but for the move from the median to the 75th percentile (or the 75th to the 90th) shows, as might be expected, slightly smaller values for the number of years of schooling equivalent measure. However the changes are insignificant and the rank order of countries is largely unchanged.

are rewarded quite differently. In some countries as one moves up thorough the quintiles there is a fairly steady increase in earnings, particularly after the initial leap, for example in Northern Ireland. However in Slovenia the biggest increase is associated with being in the fourth quintile.

In many countries movements up the distribution of literacy scores continues to reap dividends – movement from the fourth to the fifth quintile in Great Britain is more rewarding than the earlier transitions: in other words the marginal return to functional literacy is increasing at this portion of the distribution. Similar results are found in the US and Netherlands. In general the gains appear modest between middle quintiles, the Czech Republic being an exception. McIntosh and Vignoles (2001) use the IALS to estimate the effect of basic skills on earnings for Great Britain. However they focus on the effects of low levels of literacy, which assumes that middle through high levels can be combined. This is not always true and not for Great Britain in particular.

[INSERT FIGURE 4]

Throughout this specification formal schooling is also controlled for, thus these gains are even more surprising and certainly indicate that basic skills, as measured by this IALS score, is an important target for individual gains and perhaps therefore policy attention. More specifically, helping individuals to make transitions into the highest levels of functional literacy can make as much difference to their earnings as moving from the lowest to next level. This may be counter-intuitive because skills such as are measured in the IALS are typically labelled "basic skills" so there may be a presumption that while some minimum or basic level of these skills pays rich dividends, that there is little or no premium to increasing the skills of someone who is already highly skilled. Clearly this is not true for some countries.

So far we have assumed that the returns to education and functional literacy are independent of the levels of each other. This is clearly a strong – and testable- assumption, which has major implications. For example the authors of *The Bell Curve* argue that the returns to education were lower for those with lower innate ability, those outside the cognitive élite. Consequently they conclude that "…school is not a promising place to try to raise intelligence or to reduce intellectual differences" (p 414). However Ashenfelter and Rouse (2000) using the US' National Longitudinal Survey of Youth find that the returns to earnings do not vary with ability as measured by the Armed Forces Qualification test[11]. Cawley, Heckman, Lochner and Vytlacil (2000) find that *increases* in the college premium in the US over the 1990's are associated with those of higher ability.

As discussed earlier, the tests in IALS are not pure measures of innate ability or "intelligence" (nor are they intended to be) and will partly reflect the age, education and labour market experiences of individuals so this paper cannot address these important issues directly. Indeed the very strength of these tests is that they measure the contemporaneous ability of the individual which is what, presumably, employers are interested in.

We consider the complementarity by re-estimating our basic specification but including an interaction term for skills and years of education; the results are shown in table 4. This amounts to modifying equation (2):

$$\ln y = \beta_0 + \beta_{S'} S + \beta_A A + \beta_{SA.} .S.A + \beta_X X + e \qquad (3)$$

It follows that the marginal return to schooling depends on literacy and vice versa, for example:

$$\frac{\partial \ln y}{\partial S} = \beta_{S'} + \beta_{SA.} .A \qquad (4)$$

[11] Of course the publication of *The Bell Curve* has generated an enormous scholarly and public debate with many of its conclusions heavily criticised on either theoretical or empirical grounds. The use of AFQT as a general measure of cognitive ability is contested in Fischer, Hout, Jankowski, Lucas and Swidler (1996), chapter 3.

If $\beta_{SA}>0$ the return to schooling increases with the skills level in which case skills and schooling are *complements*, each enhances the marginal (proportionate) effect of the other. If $\beta_{SA}<0$ they are *substitutes*. By assuming log-linearity we are imposing a form of complementarity since even with no interaction term the marginal effect on the level (as opposed to the log) of each variable on the level depends on the other. For example rearranging (4) and setting $\beta_{SA}=0$ implies:

$$\frac{\partial y}{\partial S} = \beta_{S'}.y(A, S, X...) \tag{5}$$

There appears to be a general presumption that complementarity will prevail, or failing that, that the interaction should be zero. However it is not difficult to think of circumstances in which these two variables would be substitutes. Consider an employer who wants an employee to possess a set of skills some of which are imparted by formal schooling. If there is some upper-bound to the overall level of skill required then as the employee gets closer to this limit from one skill source then the marginal return to the other is likely to diminish. For example, an individual who has the required skills and formal education to be a bus-driver is unlikely to increase his productivity and hence his earnings in that occupation from gaining a university degree. The substitutability may only hold “locally”, for a given job, since after some point additional human capital or skills may translate into a better job.

The estimates of the parameters of interest in equation (4) are presented in Table 3. Since the magnitude of the interaction parameter is very small (as schooling multiplied by skills is numerically large) we multiply the estimated β_{SA} (and its standard error) by 100. The first thing to note from Table 3 is that with the exception of English speaking Canada, German speaking Switzerland and the Czech Republic the interactions are not statistically significant. In the first two cases the interaction is positive but note that that the direct effects of schooling and skills now have *negative* coefficients. In principle, this could imply negative marginal returns to education or skills but this only happens for values of the variables that are off the scale. What it does imply is a form of complementarity, high levels of each raises the return to the other. Only for the Czech Republic do we find evidence of substitutability.

[INSERT TABLE 3]

However given that many of the individual coefficients are not well determined it may be the case that the data is not informative enough to allow us to estimate all of the parameters precisely or maybe there is an interaction but it takes some other form[12]. Given that we expect the two variables to be correlated is not surprising. This issue is addressed by Cawley *et al* (2000) in the context of using AFQT. Essentially one is unlikely to see many individuals who have high education and low skill levels or vice versa. Therefore the interaction between the two may not be identified: assuming linearity as we have done "solves" the problem but may be a very strong assumption. This is not as likely to arise with the IALS skill measures precisely because they are taken later in life than traditional cognitive measures so it is quite possible to observe individuals with say low education but high skills. For example in Table 4 we show the proportion of a given skills quartile achieving a given level of education for Ireland and Hungary. One can see that in general there are relatively few observations in the "corners", Ireland is, to some extent, unusual because one observes a significant number in the highest skill level quartile who have quite low education.

[INSERT TABLE 4]

5. Conclusions

This paper estimates the effects of basic (or cognitive) skills on individual earnings for a large number of countries. Wages are not the only mechanism through which functional

[12] Green and Riddell (2003) consider some alterative interactions for the Canadian data

literacy may affect an individuals labour market chances[13]. We have taken employment as given but it seems plausible that the probability of an individual being employed may also depend on their skills (Rivera-batiz (1992), Raudenbush & Kasim (1998), Ishikawa & Ryan (2002) for example). However, in general the study of the effect of the skills measured in these tests on economic behaviour, while growing rapidly, is in its relative infancy by comparison with our understanding of factors such as education, trade unions or training. Therefore we still have a lot to learn about how best to model the relationship.

Our empirical results may be summarized as follow: including measures of skills (or functional literacy) lowers the return to formal education in general and substantially in some countries. Turning to the estimated effect of functional literacy itself, the effects vary substantially across countries but in general are quite large. With the exception of Canada they are statistically significant. The returns to schooling and the returns to skills are not correlated so it is impossible to identify labour markets which place particular emphasis on human capital: this implies that basic skills and formal education are quite different.

In most countries a one standard deviation increase in literacy increases wages by more than a year of schooling does. For some countries increasing an individual's skills level (literacy proficiency) from the 25th percentile to the median has the equivalent effect on wages as around two years of education. Allowing for skills to have a non-linear effect on earnings presents a mixed picture. In most countries, being in the second quintile of the distribution generates a sizeable wage premium over the first. Movements within intermediate quintiles of skills do not always generate higher wages while for some countries there is a substantial wage premium to being at the top of the skills distribution.

[13] Literacy is also likely to influence other outcomes, Denny (2003) shows using the same data that functional literacy is an important influence on an individual's social capital, measured as participation in voluntary and community activities

We show that the additional earnings generated by moving from the 25th to the 50th percentile of the skills distribution is in some cases equivalent to that generated by over two years of schooling but in others it is much lower: less than a half year. This might indicate a policy option in the former countries that supports the ability of adult education to compensate for low formal education. In the latter set of countries with relatively high returns to schooling, it would appear particularly important to prevent individuals leaving school early. Clearly a number of important methodological and interpretive caveats should be placed around these simplistic policy conclusions – but at the very least the results suggest that a one-size-fits-all option may not exist.

Allowing for interactions between skills and education there is also a mixed picture. For most countries it is difficult to identify separately the direct and indirect effects and for many others the marginal return of each is independent of the other. For a small number of countries there is evidence of complementarity and in one case there is evidence that education and skills are to some extent substitutes.

Typically researchers have assumed in the absence of other data that the patterns one finds in a small number of countries, such as the US and Great Britain, hold more widely. One of the strengths of the IALS is that by having internationally comparable data for a large number of countries, it is possible to find these patterns. The very richness of the data implies that that there are many other angles that could have been explored. Nonetheless the results show that functional literacy has a vitally important but variable role to play in the determination of individual earnings.

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Table 1: Descriptive statistics:

	Whole Sample		**Working Sample**	
	Mean:	Std. Dev:	Mean:	Std. Dev:
Age	35.94	11.89	36.62	11.89
Schooling	12.90	3.34	12.91	3.34
Literacy/Skills	283.61	55.79	287.28	55.79
Age Intervals:				
15 years of age	0.07	2.58	0	0.00
16 – 25	18.28	38.65	13.61	34.00
26 – 35	26.12	19.39	28.78	45.00
36 – 45	44.65	27.50	28.92	45.00
46 – 55	43.93	39.53	21.25	41.00
56 – 65	8.50	27.88	7.45	26.00
66 or older	0.15	3.85	0	0.00
Woman:	45.55	49.80	44.17	49.80
Rural:	30.30	45.96	30.64	45.96
Immigrant:	8.12	27.31	8.16	27.31
Father's Education:				
No schooling/isced 0:	7.32	26.00	6.88	25.00
isced 1:	23.11	42.00	22.97	42.00
isced 2:	31.51	46.00	33.18	47.00
isced 3:	23.44	42.00	23.54	42.00
isced 5:	5.25	22.00	5.02	22.00
isced 6/7:	9.38	29.00	8.41	28.00
Sample size	**32,021**		**25,407**	

Table 2: Estimated return to schooling, skills and respective standard errors:

	Return to Schooling β_S (1)	Standard Error	Return to Schooling $\beta_{S`}$ (2)	Standard Error	$\beta_S - \beta_{S`}$	Return to Skills β_A (3)	Standard Error	Return to Skills (Normalised) β_{AN}	Standard Error
Belgium	0.0720	0.0087	0.0570	0.0100	0.0150	0.1930	0.0611	0.0960	0.0304
Canada (English)	0.0660	0.0171	0.0520	0.0176	0.0140	0.1410	0.0986	0.0820	0.0573
Canada (French)	0.1070	0.0286	0.0880	0.0461	0.0190	0.1830	0.2473	0.0960	0.1297
Chile	0.0820	0.0086	0.0600	0.0103	0.0220	0.2440	0.0683	0.1310	0.0367
Czech	0.1190	0.0121	0.0990	0.0127	0.0200	0.2660	0.0721	0.1170	0.0317
Denmark	0.0590	0.0051	0.0470	0.0058	0.0120	0.1970	0.0440	0.0740	0.0165
Finland	0.0450	0.0055	0.0340	0.0059	0.0110	0.2060	0.0425	0.0820	0.0169
Germany	0.0540	0.0104	0.0490	0.0106	0.0050	0.1310	0.0682	0.0530	0.0276
Great Britain	0.1000	0.0093	0.0780	0.0094	0.0220	0.2600	0.0455	0.1370	0.0240
Hungary	0.0860	0.0120	0.0720	0.0131	0.0140	0.1860	0.0845	0.0790	0.0359
Ireland	0.0790	0.0091	0.0540	0.0096	0.0250	0.3180	0.0477	0.1680	0.0252
Italy	0.0520	0.0071	0.0360	0.0082	0.0160	0.1950	0.0519	0.1080	0.0287
Netherlands	0.0440	0.0061	0.0300	0.0066	0.0140	0.3280	0.0547	0.1290	0.0215
New Zealand	0.0580	0.0086	0.0410	0.0094	0.0170	0.2440	0.0471	0.1180	0.0228
Northern Ireland	0.1110	0.0098	0.0900	0.0104	0.0210	0.2640	0.0461	0.1450	0.0253
Norway	0.0600	0.0060	0.0480	0.0067	0.0120	0.1720	0.0489	0.0670	0.0190
Slovenia	0.1540	0.0134	0.1380	0.0146	0.0160	0.1530	0.0591	0.0860	0.0332
Sweden	0.0360	0.0066	0.0280	0.0069	0.0080	0.1790	0.0442	0.0810	0.0200
Switzerland (French)	0.0480	0.0088	0.0380	0.0092	0.0100	0.2120	0.0682	0.0890	0.0286
Switzerland (German)	0.0530	0.0111	0.0340	0.0119	0.0190	0.2900	0.0730	0.1460	0.0368
USA	0.0890	0.0081	0.0620	0.0088	0.0270	0.2980	0.0440	0.1760	0.0260

Controls used in regressions: female, rural, immigrant, & dummies for father's education using ISCED levels.

(1) Not controlling for skills

(2) Controlling for skills

(3) Skills in units of 100

Table 3 Returns to schooling, skills and an interaction term with respective standard errors:

	Schooling: $\beta_{S`}$	Standard Error:	Skills: β_{A}	Standard Error:	Interaction: β_{AS}	Standard Error:
Belgium	0.0615	0.0371	0.2118	0.1630	-0.1516	1.2633
Canada (English)	-0.0763	0.0652	-0.3875	0.2808	4.3798	2.0856
Canada (French)	0.1809	0.1533	0.5559	0.4211	-3.3431	4.5177
Chile	0.0645	0.0304	0.2626	0.1375	-0.1946	1.2975
Czech	0.2568	0.0859	0.9120	0.3648	-5.2108	2.8319
Denmark	-0.0090	0.0348	-0.0301	0.1503	1.9117	1.1657
Finland	0.0707	0.0345	0.3496	0.1382	-1.2241	1.1334
Germany	-0.0054	0.0676	-0.0723	-0.2678	1.7906	2.3874
Great Britain	0.0927	0.0515	0.3163	0.2067	-0.4719	1.6855
Hungary	0.0132	0.0601	-0.0883	0.2848	2.2240	2.2020
Ireland	0.1222	0.0433	0.5624	0.1524	-2.3969	1.4615
Italy	0.0648	0.0272	0.2937	0.1023	-1.0910	0.9919
Netherlands	0.0935	0.0354	0.5774	0.1484	-2.1426	1.1903
New Zealand	-0.0045	0.0567	0.0612	0.2039	1.5335	1.8042
Northern Ireland	0.1596	0.0585	0.5457	0.2293	-2.3076	1.8610
Norway	-0.0103	0.0357	-0.0439	0.1371	1.9209	1.1503
Slovenia	0.0794	0.0481	-0.0972	0.1984	2.3573	1.8561
Sweden	0.0454	0.0355	0.2413	0.1277	-0.5688	1.1375
Switzerland (French)	0.0707	0.0462	0.3464	0.2074	-1.1386	1.6266
Switzerland (German)	-0.0426	0.0374	-0.0218	0.1680	2.8052	1.3684
USA	0.0188	0.0285	0.0960	0.1315	1.4949	0.9461

Note: The numbers in the last two columns have been multiplied by 100.

Table 4: Cross tabulation of schooling by quartiles of skill level for 2 countries:

	Ireland:				**Hungary:**			
Schooling:	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
5 to 9 years	59.53	32.68	22.96	9.73	31.28	14.23	7.32	2.44
10 to 12 years	31.52	49.81	49.81	38.52	51.85	58.54	58.13	31.3
14 to 17 years	8.17	16.34	24.9	42.41	13.99	21.95	24.8	44.31
16+ years	0.78	1.17	2.33	9.34	2.88	5.28	9.76	21.95

Figure 1 RATES OF RETURN TO SCHOOLING

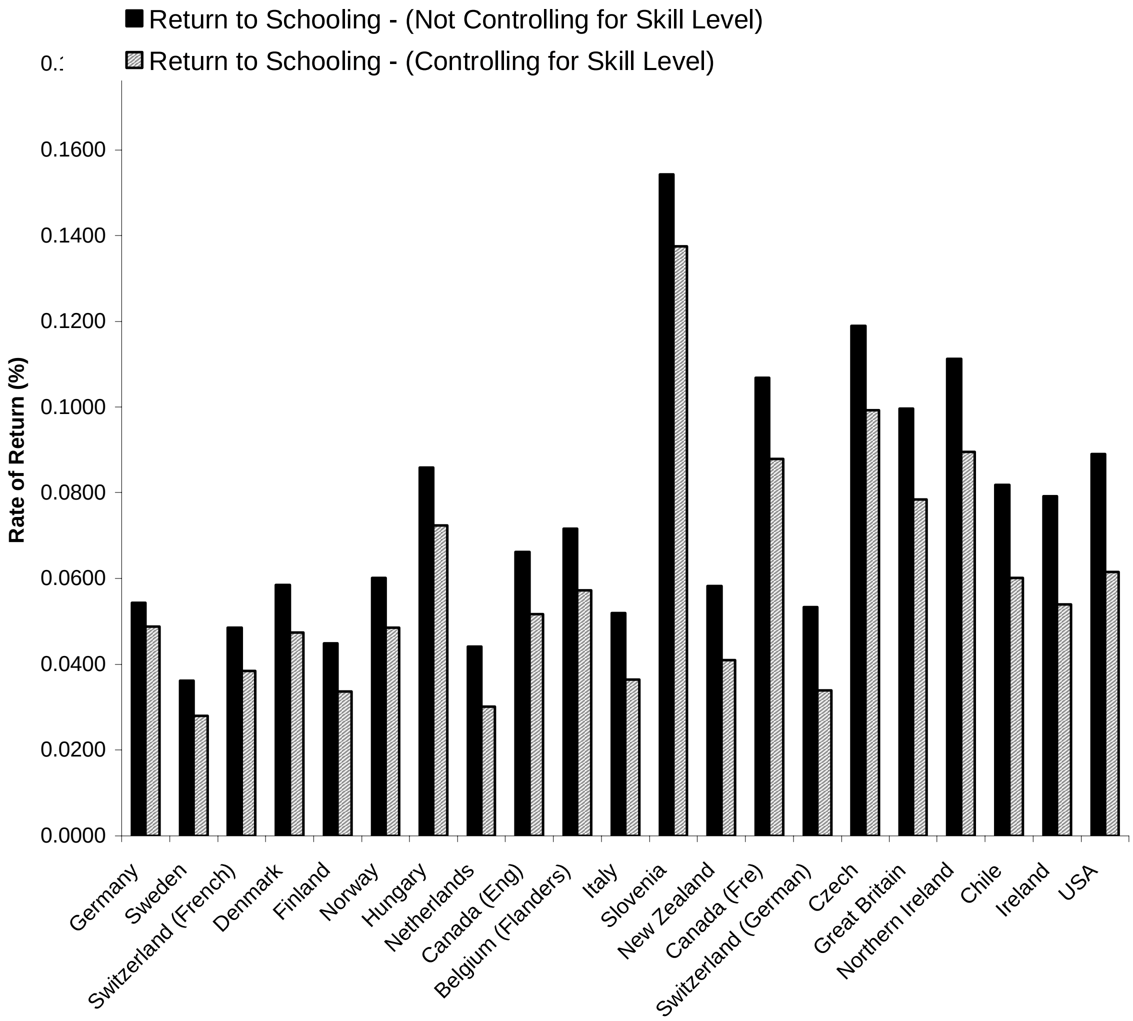
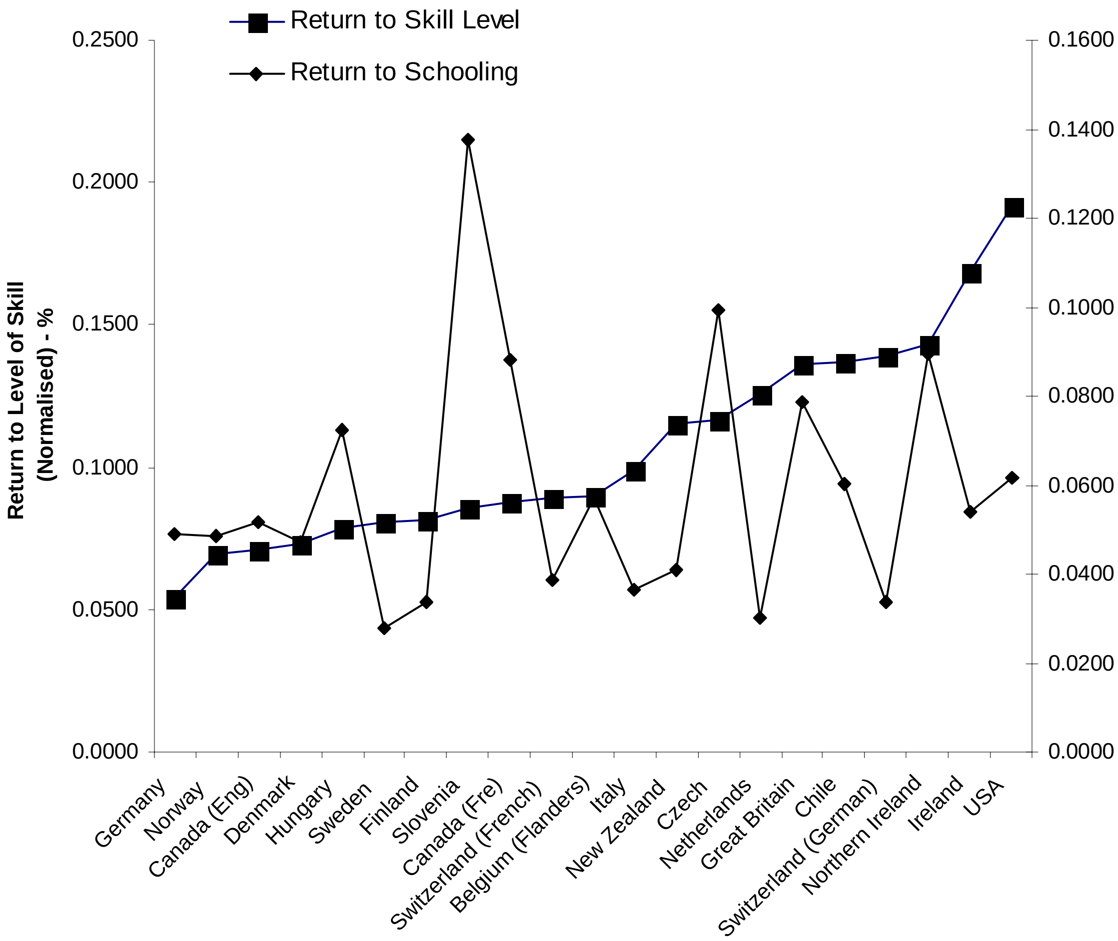
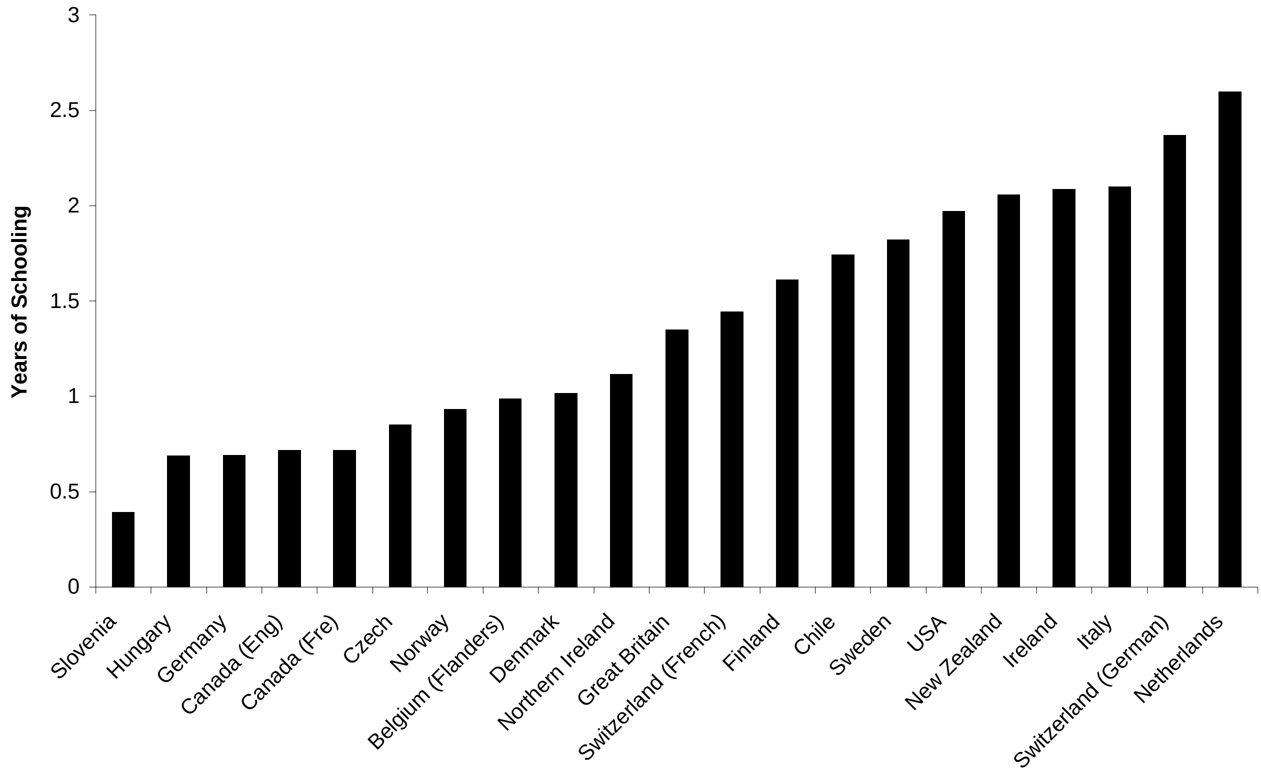


Figure 2   *RATES OF RETURN TO SKILLS (normalised)*



Note: This figure shows β_{AN} from Table 2 relative to the left hand axis and $\beta_{s'}$ relative to the right hand axis.

Figure 3: YEARS OF SCHOOLING EQUIVALENT TO MOVE FROM 25TH TO 50TH PERCENTILE OF THE SKILLS DISTRIBUTION

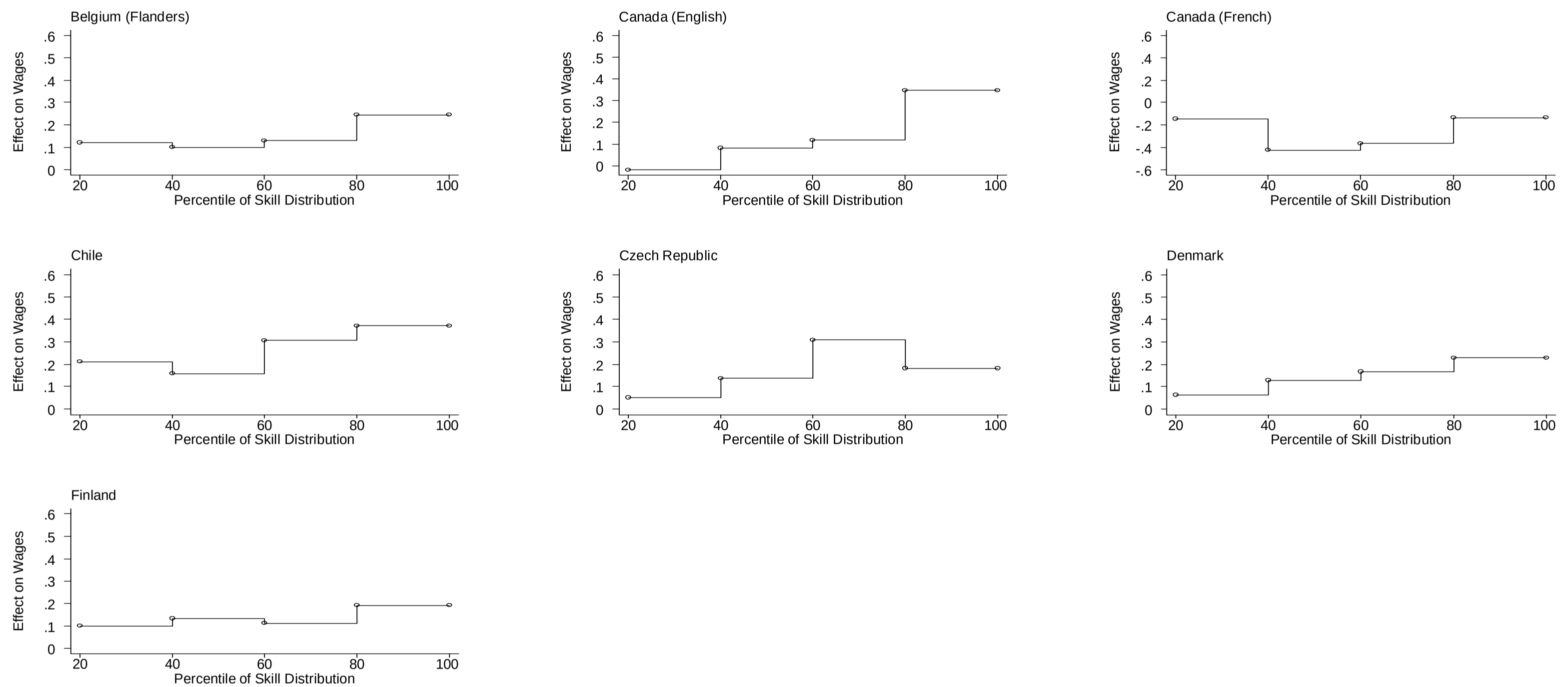


Note: The graph above solves for S in the equation below, where S is the number of years schooling of an individual and Q_{50} and Q_{25} are the 50th and 25th percentile of the skills measure respectively. $\beta_{S'}$ and β_A are the estimated returns for each country taken from Table 2 as described in equation (2).

$$\beta_{S'} S = \beta_A (Q_{50} - Q_{25})$$

Figure 4

Return to Quintiles of Skill Distribution (first quintile omitted)



Note: The graphs show the estimated coefficient on a dummy variable representing the quintile of the skills distribution of an individual. The vertical access represents the proportionate effect on wages i.e. 0.1= 10%

Figure 4 (cont.)

Return to Quintiles of Skill Distribution (first quintile omitted)

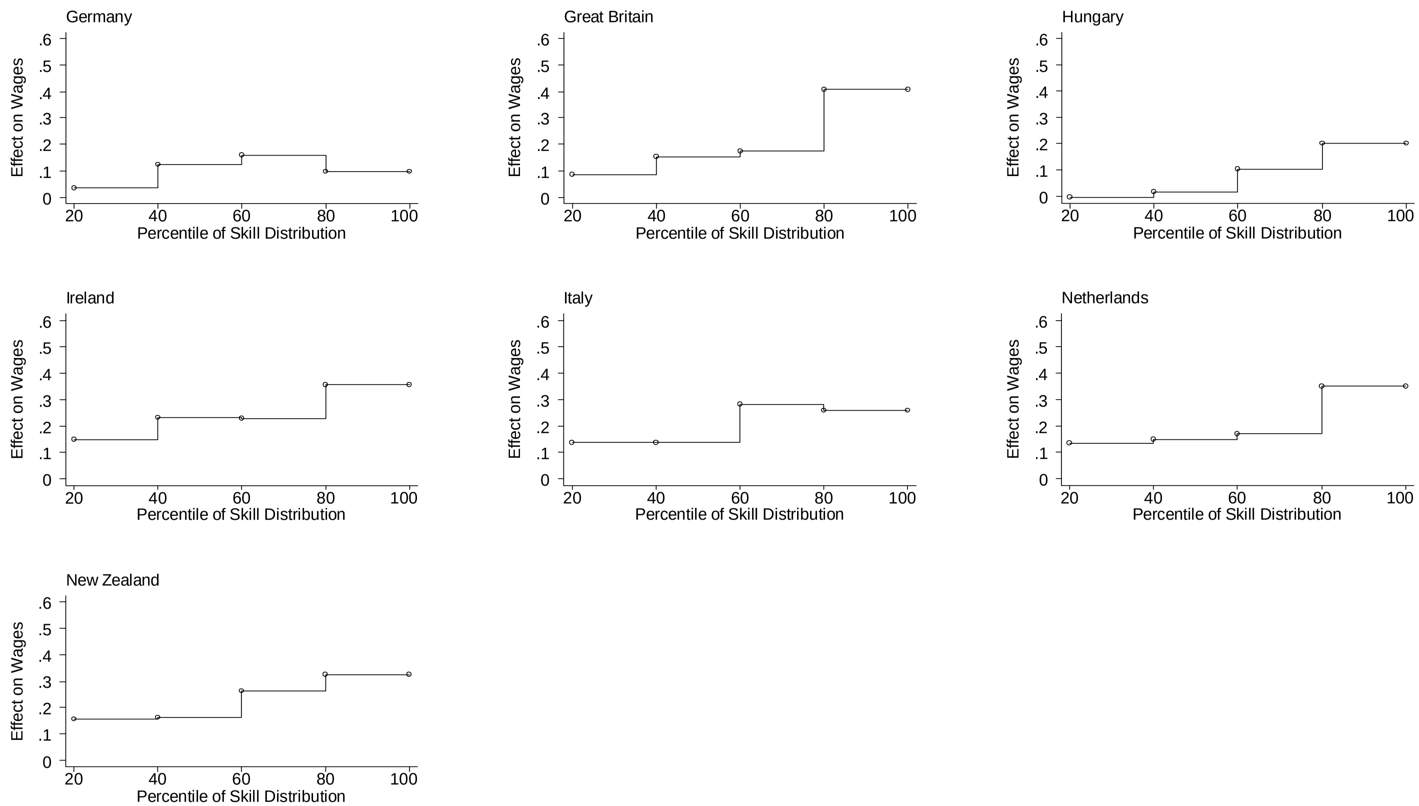


Figure 4 (cont.)

Return to Quintiles of Skill Distribution (first quintile omitted)