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Functional Literacy, Educational Attainment and Earnings: A Multi-Country Comparison

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Functional literacy, educational attainment and earnings: a multi-country comparison*

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Abstract:

In this paper a rich and innovative dataset, the International Adult Literacy Survey, is used to examine the impact of functional literacy on earnings. We show that the estimated return to formal education is sensitive to the inclusion of literacy: excluding it biases the return to education in many countries by significant amounts. Literacy itself has a well-determined effect on earnings in all countries though with considerable variation in the size of the effect. The benefits of literacy do not only arise from increasing low levels of literacy: increases at already high levels generate substantial increases in earnings in some countries. In general we find little interaction between schooling and literacy though for a few countries they appear to complement each other.

* Material from the International Adult Literacy Survey is used with permission of Statistics Canada who bears 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. Denny is also affiliated with the IFS, London and Harmon with CEPR & IZA. Harmon acknowledges the award of the Nuffield Foundation New Career Development Fellowship at University College London. Corresponding author: Dr. Kevin Denny, Department of Economics & Institute for the Study of Social Change, University College Dublin, Belfield, Dublin 4, Ireland. Phone (+353 1) 716 4613. Fax (+3531) 716 1108, kevin.denny@ucd.ie .

1. Introduction

This paper examines the effect of functional literacy on individual earnings using the IALS. Since there may be numerous determinants of earnings we estimate multivariate models allowing in particular for the impact of formal education. There is an enormous econometric literature estimating the impact of education. This is usually referred to as the "return to schooling" since it was shown by Mincer in his classic 1974 study that the estimated marginal effect of a year's education was equivalent, under certain conditions to the internal rate of return treating education as an investment by the individual[1].

Over the 1990's there has been a sustained and sizeable increase in the return earned by college graduates relative to the less educated contributing to increased inequality. One explanation for this is that increased globalisation of markets has put downward pressure on the wages of low skill workers because of competition with low wage economies. An alternative view is that changes in the workplace, particularly 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 is beyond the remit of this paper[2]. Either way it is clearly important to know what the returns to skills are if policy makers are to make the correct decisions about the provision of training.

There is a much smaller body of research estimating the effects of characteristics such as innate abilities like "intelligence". This is partly due to the lack of suitable data, especially outside the United States. Furthermore in much of the economic literature on skills, "high skill" is actually *defined* according to the highest education level completed and not by direct measure.

[1] The most important assumption is that there is no direct cost of tuition.

This has, to some extent, changed in the last ten years or so partly reflecting the controversy caused by Herrnstein & Murray's monograph *The Bell Curve* (1994) but also by changes in labour markets particularly, but not exclusively, in the US. *The Bell Curve* argued for the importance of increasing importance of innate skills in the labour market. Those that possessed these skills formed the "cognitive elite" and policies which aimed to increase the non-innate skills of the outside the elite were judged to be unproductive. These results are hotly disputed by leading scholars, for example after a careful examination of US data, Ashenfelter & Rouse (2000) find no evidence that that the return to schooling varies with the measured ability of individuals.

In all this of this discussion we have used the terms like ability, skills, cognitive skills rather loosely and interchangeably but one needs to be quite clear that there are different underlying concepts. One can usefully distinguish between innate abilities such as intelligence and acquired abilities such as literacy. The former are those with which one is born and are presumably stable over time. On the other hand skills are something that can be acquired through education and training but it seems likely that they are correlated with some inherited abilities: "smart" people are likely to find it easier to acquire additional skills or may better appreciate the benefits of it. Measures of innate ability should therefore be assessed early in the life of the individuals before they are "corrupted" by educational and other interventions. Furthermore this is explicitly not what the tests were designed to do. Measures of skills such as those used in this paper clearly will reflect, to some extent, the innate ability of an individual but should not be interpreted as a general measure of intelligence. Indeed the term "cognitive skill", used in Pryor & Schaeffer (1999) study based on NALS, reflects the somewhat ambiguous position of these tests.

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

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

Studies on the determinants of earnings are typically based on standard Mincer (1974) log-linear earnings equations show that returns to education are around 6% to 8% per school year for men [3]. A useful extension to the core model is to consider the role of the individual's ability on the schooling decision whilst preserving the basic idea of the Mincer model of schooling being an investment.

Griliches (1977) introduces ability explicitly into the derivation of the log-linear earnings function. In the basic model the internal rate of return (IRR) of schooling is partly determined by foregone income (less any subsidy such as parental contributions) and any educational costs. Introducing ability differences has two effects on this basic calculus. The more able individuals may be able to 'convert' schooling into human capital more efficiently than the less able, and this raises the IRR for the more able. One might think of this as inherent ability and education being 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 IRR.

Moreover, empirically least squares estimation requires that the explanatory variables are uncorrelated with the unobserved disturbance term in the equation. 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. The approaches adopted to deal with this issue typically include explicit measures for ability to proxy for unobserved ability (Blackburn & Neumark, 1993). IQ and other such tests are an example of such proxies (Griliches (1977), Griliches & Mason (1972)). The results of these studies have largely found favour with the notion of upward bias in least squares results. Griliches (1977), using NLSY data which includes test scores from IQ tests conducted in high school in addition to a survey-specific test initiated at the first interview, finds significant reduction in the estimated return to schooling once ability measures are included. More recent studies by McKinley Blackburn and David Neumark (1993, 1995) suggest a similar finding. Again using NLSY data they find the OLS estimates to be some 30-40% higher when ability measures are excluded. Finally Murnane, Willett & Levy (1995) use mathematics ability as a regressor and find evidence of upward bias of between 31-52%.

Boissiere, Knight & Sabot (1985) find that the return to education drops by two-thirds, once cognitive skills 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 & Vytlacil (1996) find that a measure of general intelligence calculated using the technique of 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.

[3] See Harmon, Oosterbeek & Walker (2003) and Heckman, Lochner & Todd(2003) for recent overviews of the literature on the return to schooling .

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 are the appropriate variable. With either a signalling 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 often worth about three of four years worth of education)[4]. 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 ability, 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 ability is denoted $\beta_{S'}$. In some cases we estimate a variant of (2) where the ability 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 $\beta_{S'}$.

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

3. The IALS Data Set & Ability Measures

The International Adult Literacy Survey (IALS) was administered by twelve governments in association with the European Union, the OECD and UNESCO in a series of waves between 1994 and 1996. A further wave in 1998 added eight more countries[5]. 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 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 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 survey consists for most countries of a sample of 2000 to 3000 from the adult civilian population aged between 16 and 65. The language of interview is each country's respective national language. Sample design was the responsibility of each country. The IALS is structured around three stages. Firstly, each individual was required to complete a background questionnaire, which provided information on age, sex, education, labour market experiences and literacy related activities. An individual was deemed to be an IALS respondent if they partially or fully completed the background questionnaire. Stage 2 involved the completion of 6 simple assignments; if the respondent answered incorrectly on more than two of these tasks the interview was terminated. This

[5] The countries involved initially 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.

was in order to avoid re-interviewing those individuals of whom it is known that their literacy level is already very low (known as Level 1). Lastly a main booklet of tasks was given to each respondent which resulted in a score, which measured their literacy level. All assignments required the respondent to use materials from everyday life. For example, instructions from medicine bottles, the completion of order forms and reading a newspaper listed amongst the tasks that were required in order to complete the test questionnaire.

The literacy level 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, which is subsequently subdivided into five levels. Level 1 has a score range from 0-225 and would indicate very low levels where, for example, instructions for a medicine prescription would not be understood. The interval 226-275 defines Level 2 where individuals are limited to handling material that is not too complex and clearly defined. Level 3 ranges from 276-325 and is considered the minimum desirable threshold for most countries while Level 4 (326-375) and Level 5 (376-500) show increasingly higher skills which integrate several sources of information or solve complex problems.

As an example a task that involves reading the dosage on a medicine label falls into level 1 of the prose scale, whereas a level 4 task in the prose scale may require the respondent to answer questions from a set text. A level 1 task in the Quantitative scale may require the interviewee to add up the total number of goods ordered from an order form, while a level 4 task on the same scale may ask the respondent to calculate the total return from a compound interest table on a certain amount (OECD 1997). To be classified at a particular level the respondent had to answer uniformly at that level. The criterion used for consistent performance was 80 per cent. The lower the score the respondent received at each scale, the lower the level and hence the lower one's measure of literacy at that scale.

In constructing the scores each country was instructed to re-score 20 per cent of tests with a 95 per cent degree of accuracy to guarantee precision of results. In addition, to ensure good quality inter-country scores a different country re-scored 10 per cent of another country's scores. The IALS were also very conscious of non-response bias. Interviewers were advised to return to households that did not give a response as many times as possible and the sample was carefully weighted to known population variables. The survey makes uses of "plausible value" sampling methodology which provides five measures of each of the three variables (prose, document and quantitative literacy) based on the fact that individuals will answer different parts of a given question. Given that each of the five is equally plausible we use the simple average to construct measures of prose, document and quantitative ability.

IALS provides us with a unique opportunity to analyse this issue 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 hourly 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 & White (see Gould & 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 functional literacy.

Our measure of functional literacy is simply the average over the three types of literacy: prose, document and quantitative. 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[6]. 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 just 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 US' National Adult Literacy Survey, one of the precursors to IALS, casts doubt on whether those tests identified distinct types of functional literacy.

Table 1 shows standard descriptive statistics for the full sample and the sample used in the econometric analysis[7]. 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.

[6] This is consistent with the results for Canadian IALS in Green & Riddell (2003).

[7] 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.

4. The results

The estimates of the return to education from these simple earnings equations are presented in Figure 1. Here we summarise the earnings returns from education from our basic specification both excluding and including our ability measure. The data presented in the table is sorted in ascending order of the *differences* in the return from including ability. 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 & Lydon (2002). For example less developed or transition economies tend to have higher returns to education and this is borne out in Figure 1.

However what appears to be the most interesting aspect of this figure is the quite dramatic drop in the return when ability is included in some countries and that in particular the countries at the bottom end of the table where the impact of including ability is low or insignificant are all from non-English speaking countries. That the return to schooling falls with the inclusion of ability reflects the fact those with higher education will in general have higher literacy so omitting literacy exaggerates or biases upwards the estimated impact of schooling.

The alternative issue is to focus on the return to ability in these countries. To make the coefficient of this comparable across countries we also normalise the ability score to have mean zero and a standard deviation of one. Figure 2 presents the earnings return to this normalised measure of ability. Again the return to ability is highest in English speaking countries (Ireland, Great Britain, USA) in general

However while these returns are significant it should be noted that the shift in scores required to move an individual one standard deviation is significant. Moreover the presentation of these results is sensitive to the distribution of the test scores. If all countries had normally distributed test scores of similar dispersion Figure 2 could be interpreted along all parts of the score distribution.

However if there is variation in the dispersion of the scores or skewness in the distribution this may not hold.

Figure 3 shows the earnings return from moving from the 25th to the 50th percentile (or median) of the score 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 might be thought of as the key issue from a policy maker's perspective. The return to a year of schooling is clear and well defined measure. If a policymaker is trying to counteract low schooling by later interventions to raise basic skills they need to know that that a basic skills programme is going to reap dividends particularly given the variance in returns to these skills across the distribution of test scores as shown in Figures 2. Figure 3 is not reassuring on these matters given the wide variation in the number of years of schooling required to equate to a standard deviation shift in scores. It again would appear, with the exception of the Netherlands, that the English speaking countries stand to gain the most from raising the skills level from low to median levels. For example individuals in the USA who can make this move receive an earnings return equivalent to almost three schooling years. For Nordic countries on the other hand, a significant shift in scores of this type only equates to under a year of schooling[8].

There is little evidence that countries with low returns to education have low returns to ability or vice versa. In fact the direct effects seem largely independent of each other across countries. The correlation between the two sets of coefficients is not statistically significant.

[8] 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.
There is little evidence that countries with low returns to education have low returns to ability or vice versa. In fact the direct effects seem largely independent of each other across countries. The correlation between the two sets of coefficients is not statistically significant.

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. The results, summarised in Figure 4, are most interesting. The first coordinate in each chart gives the return in moving the first to the second quintile, i.e. from very low to low levels of functional literacy. The return from this move can be as low as 5% for an individual, and is more typically in the region of 10-15%. However the United States in particular has an enormous gain from escaping this bottom level of literacy of the order of 30%.

In many countries movements up the distribution of literacy scores continues to reap dividends – movement from the second to third quintile in Great Britain is more rewarding than this earlier transition (i.e. the marginal return to literacy is increasing at this portion of the distribution). In general however the gains appear modest through these middle quintiles. This changes when we examine the gains from very high levels of functional literacy – the transition into the top quintile seems to generate quite substantial gains. In some countries (Ireland, GB, Netherlands for example) this return is of the order of 15% and compared with the bottom quintile, individuals at the top levels earn almost 50% more.

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 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 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 & Rouse (2000) using the US' National Longitudinal Survey of Youth find that the returns to earnings does not vary with ability as measured by the Armed Forces Qualification test[9]. Cawley, Heckman, Lochner & 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" and will partly reflect the age, education and labour market experiences of individuals so this paper cannot address these important issues directly. We examine this by re-estimating our basic specification but including an interaction term for ability and years of education; the results are shown in table 4. This amount 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:

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

[9] 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 disputed in Fischer, Hout, Jankowski, Lucas & Swidler (1996), chapter 3.

If $\beta_{SA}>0$ the return to schooling increases with the ability level in which case ability 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 ability 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 most of the interactions are not statistically significant. However one needs to take into account the joint significance of sets of variables to draw interesting inferences, in all cases the three are jointly significant. There are in fact four distinct groups of countries in these results.

For Norway, the US and the two Canada samples: the interaction term is significant and the main effects are not jointly significant. We define this as “strong complementarity”: the marginal benefit of either is proportional to the other. In other words only the educated benefit from having higher ability and vice versa. The second “group” consists of Ireland, There the interaction term is negative and significant and the main effects are jointly significant so the marginal effect of each diminishes with the other. This is the substitutability argument discussed earlier[10].

For a large group of countries (Chile, Czech Republic, Finland, Italy, Netherlands, New Zealand and Slovenia) the main effects are jointly significant but the interaction is not, in which case one can infer that the marginal returns are independent.

For the remaining countries (Belgium, Denmark, Germany, Great Britain, Hungary, Northern Ireland, Sweden and the two Swiss samples), while the interaction is not statistically significant, the two direct effects of literacy and schooling are not jointly significant either. This does not imply that they are not matter, it may well be the case that the data is not informative enough to allow us to estimate all of the parameters precisely or it maybe there is an interaction but it takes some other form. 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 ability 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

[10] In principle this could imply negative marginal returns to education or ability but this only happens for values of the variables that are off the scale.

possible to observe individuals with say low education but high skills. For example In Table 4 we show the proportion of a given ability 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 extent unusual because one observes a significant number in the highest ability quartile who have quite low education.

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 literacy may affect an individuals labour market chances[11]. We have taken employment as given but it seems plausible that the probability of an individual being employed may also depend on their cognitive skills (Rivera-batiz (1992) and Raudenbush & Kasim (1998)). 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 ability 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.

In all but two countries (Slovenia and the Czech Republic) a one standard deviation increase in literacy increases wages by more than a year of schooling does. For some countries increasing an individual's ability from the 25th percentile to the median has the equivalent effect on wages as around two years of education. These countries are mostly English speaking. Allowing for ability 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 ability do not always generate higher wages while for some countries there is a substantial wage premium to being at the top of the ability distribution.

Allowing for interactions between ability and education there is also a mixed picture. For many 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

[11] Literacy is also likely to influence other outcomes, Denny (2003) shows using the same data that functional literacy 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.

an important influence on an individual’s social capital, measured as participation in voluntary and community activities.

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Table 1: Descriptive statistics:

	Whole Sample		Working Sample	
	Mean:	Std. Dev:	Mean:	Std. Dev:
Age	37.87	11.83	38.78	11.05
Schooling	12.63	3.35	12.62	3.18
Ability	283.64	52.64	285.71	51.11
Age Intervals:				
15 years of age	0.07	0.03	0	0.00
16 – 25	18.39	0.39	13.61	0.34
26 – 35	27.18	0.44	28.78	0.45
36 – 45	26.94	0.44	28.92	0.45
46 – 55	19.37	0.40	21.25	0.41
56 – 65	7.87	0.27	7.45	0.26
66 or older	0.18	0.04	0	0.00
Woman:	47.94	0.50	46.87	0.50
Rural:	33.51	0.47	32.7	0.47
Immigrant:	6.25	0.24	6.24	0.24
Father's Education:				
No schooling/isced 0:	7.32	0.26	6.88	0.25
isced 1:	23.11	0.42	22.97	0.42
isced 2:	31.51	0.46	33.18	0.47
isced 3:	23.44	0.42	23.54	0.42
isced 5:	5.25	0.22	5.02	0.22
isced 6/7:	9.38	0.29	8.41	0.28
Sample size	**32,002**		**24,978**	

Table 2: estimated returns:

	Return to Schooling β_S	Standard Error	Return to Schooling $\beta_{S`}$	Standard Error	$\beta_S - \beta_{S`}$	Return to Ability β_A	Standard Error	Return to Ability (Normalised) β_{AS}	Standard Error
Belgium	0.0832	0.0079	0.0697	0.0089	0.0135	0.1823	0.0555	0.0845	0.0089
Canada (English)	0.0881	0.0082	0.0715	0.0094	0.0166	0.1777	0.0511	0.0894	0.0094
Canada (French)	0.1013	0.0121	0.0806	0.0151	0.0207	0.2230	0.1012	0.1068	0.0151
Chile	0.0932	0.0071	0.0679	0.0089	0.0252	0.2717	0.0598	0.1526	0.0089
Czech	0.1172	0.0109	0.1011	0.0117	0.0161	0.2355	0.0700	0.1033	0.0117
Denmark	0.0598	0.0050	0.0489	0.0055	0.0109	0.1923	0.0420	0.0712	0.0055
Finland	0.0459	0.0050	0.0351	0.0055	0.0108	0.1988	0.0443	0.0783	0.0055
Germany	0.0536	0.0082	0.0445	0.0085	0.0091	0.2256	0.0611	0.0931	0.0085
Great Britain	0.1020	0.0076	0.0747	0.0080	0.0273	0.3422	0.0410	0.1796	0.0080
Hungary	0.0911	0.0112	0.0774	0.0124	0.0136	0.1934	0.0791	0.0819	0.0124
Ireland	0.0812	0.0083	0.0551	0.0088	0.0262	0.3275	0.0470	0.1734	0.0088
Italy	0.0524	0.0058	0.0416	0.0066	0.0109	0.1519	0.0459	0.0772	0.0066
Netherlands	0.0480	0.0051	0.0353	0.0054	0.0127	0.3123	0.0507	0.1196	0.0054
New Zealand	0.0589	0.0072	0.0391	0.0075	0.0198	0.3063	0.0412	0.1450	0.0075
Northern Ireland	0.1114	0.0079	0.0881	0.0082	0.0233	0.2992	0.0405	0.1625	0.0082
Norway	0.0641	0.0056	0.0535	0.0064	0.0105	0.1550	0.0461	0.0624	0.0064
Slovenia	0.1520	0.0111	0.1361	0.0126	0.0159	0.1448	0.0578	0.0811	0.0126
Sweden	0.0361	0.0062	0.0280	0.0065	0.0081	0.1746	0.0462	0.0783	0.0065
Switzerland (French)	0.0563	0.0086	0.0473	0.0092	0.0090	0.1912	0.0728	0.0802	0.0092
Switzerland (German)	0.0584	0.0109	0.0414	0.0116	0.0170	0.2707	0.0716	0.1297	0.0116
USA	0.0834	0.0064	0.0545	0.0071	0.0290	0.3023	0.0373	0.1951	0.0071

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

(1) Not controlling for ability

(2) Controlling for ability

(3) Ability in units of 100

Table 3 Schooling, ability and an interaction term:

		Schooling: β_{S}	Standard Error:	Ability: β_{A}	Standard Error:	Interaction: β_{AS}	Standard Error:
Belgium	4	0.0811	0.0017	0.2337	0.0355	-0.3943	1.3792
Canada (English)	1	0.0007	0.0012	-0.1124	0.0213	2.4124	1.1418
Canada (French)	1	-0.0627	0.0035	-0.3431	0.0612	5.0442	2.0278
Chile	3	0.0726	0.0006	0.2906	0.0121	-0.2052	1.0047
Czech	3	0.2248	0.0054	0.7596	0.0995	-4.1141	2.4071
Denmark	4	-0.0038	0.0011	-0.0231	0.0201	1.7807	1.1190
Finland	3	0.0765	0.0012	0.3600	0.0196	-1.3679	1.1269
Germany	4	0.0009	0.0027	0.0607	0.0420	1.4633	1.7362
Great Britain	4	0.0653	0.0022	0.3044	0.0353	0.3134	1.5217
Hungary	4	0.0466	0.0032	0.0520	0.0707	1.1682	2.0987
Ireland	2	0.1294	0.0015	0.5935	0.0199	-2.6142	1.3019
Italy	3	0.0804	0.0007	0.3027	0.0116	-1.4738	0.9521
Netherlands	3	0.0914	0.0012	0.5369	0.0212	-1.8800	1.1419
New Zealand	3	-0.0298	0.0017	0.0316	0.0282	2.2787	1.3513
Northern Ireland	4	0.0985	0.0022	0.3421	0.0388	-0.3431	1.5397
Norway	1	-0.0165	0.0013	-0.1143	0.0208	2.3060	1.1706
Slovenia	3	0.0721	0.0018	-0.1291	0.0342	2.5857	1.6590
Sweden	4	0.0503	0.0012	0.2535	0.0168	-0.7229	1.1098
Switzerland (French)	4	0.1197	0.0024	0.5055	0.0492	-2.5257	1.6819
Switzerland (German)	4	-0.0337	0.0021	-0.0435	0.0400	2.7269	1.6235
USA	1	0.0038	0.0005	0.0549	0.0121	1.8555	0.7781

Note: The numbers in the last two columns have been multiplied by 100. **1** beside country name implies interaction significant, main effects not. **2** implies main effects and interaction significant. **3** implies main effect significant but interaction not. **4** implies main effects not significant and interaction not.

Table 4: Cross tabulation of schooling by ability 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

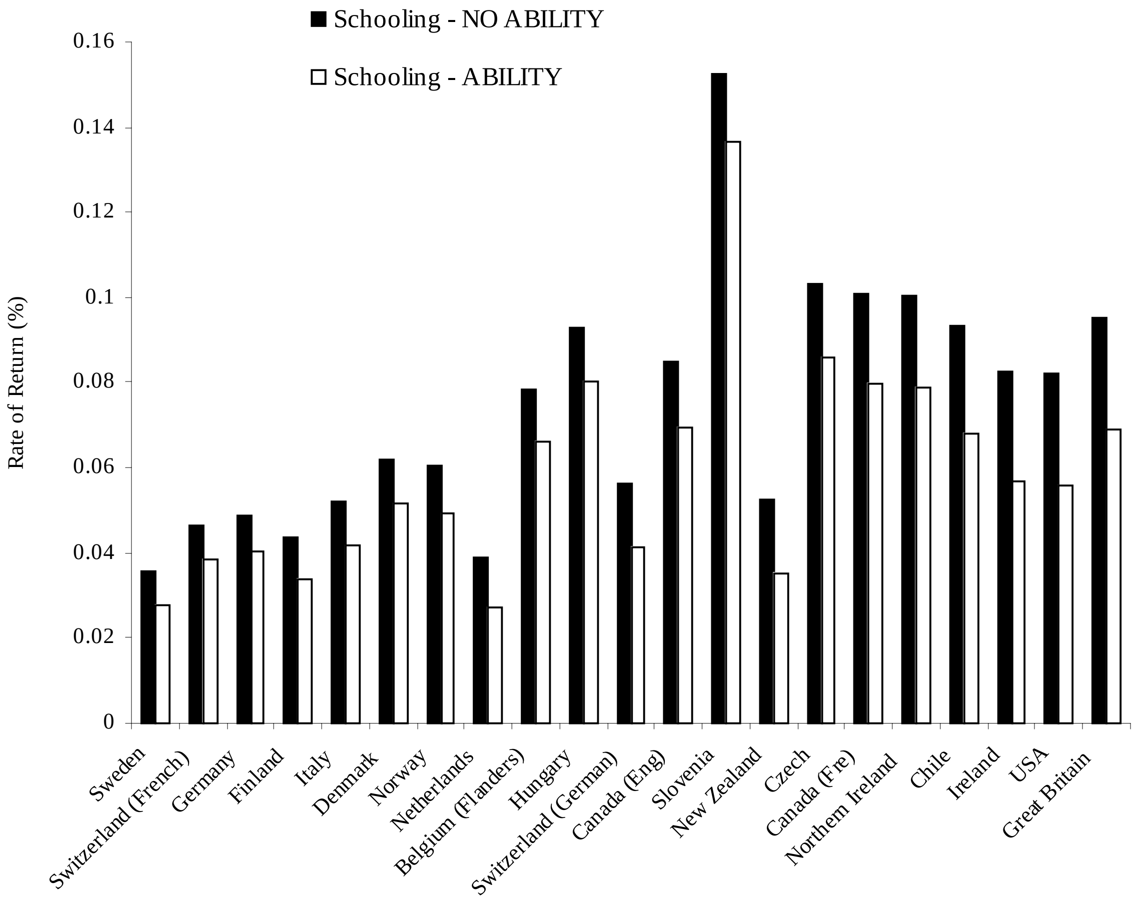
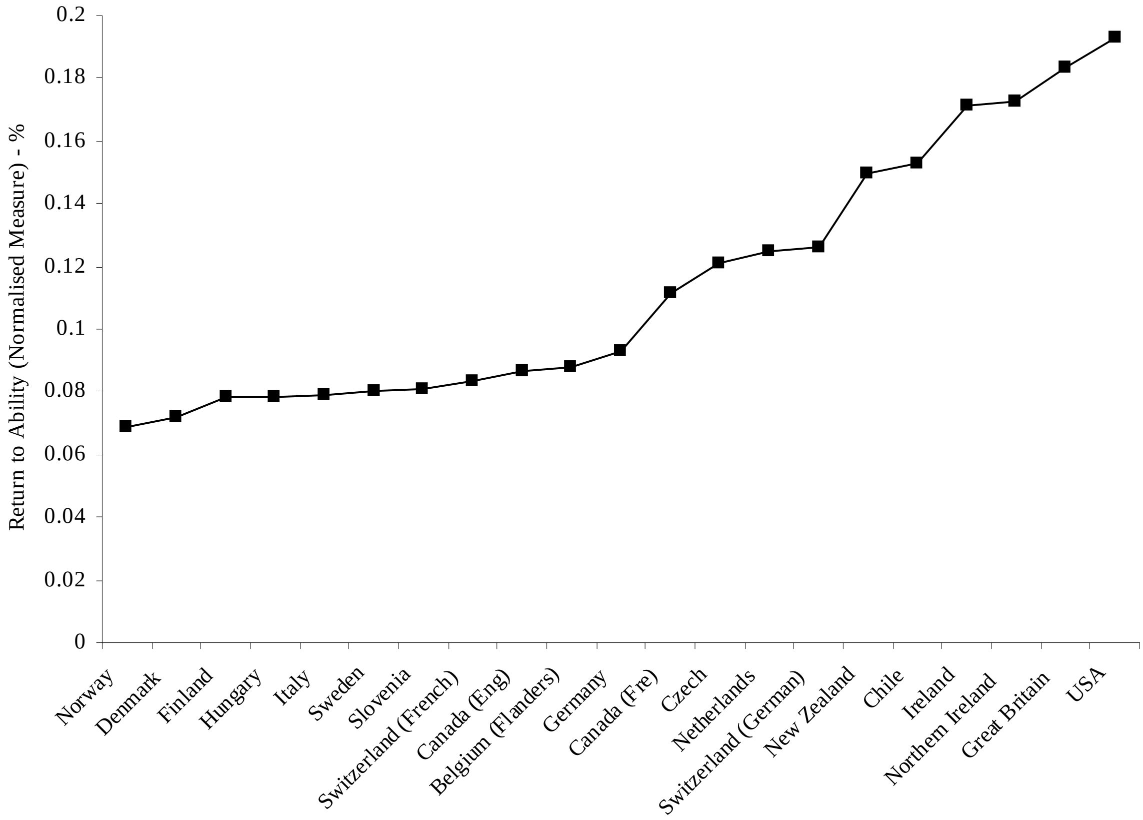
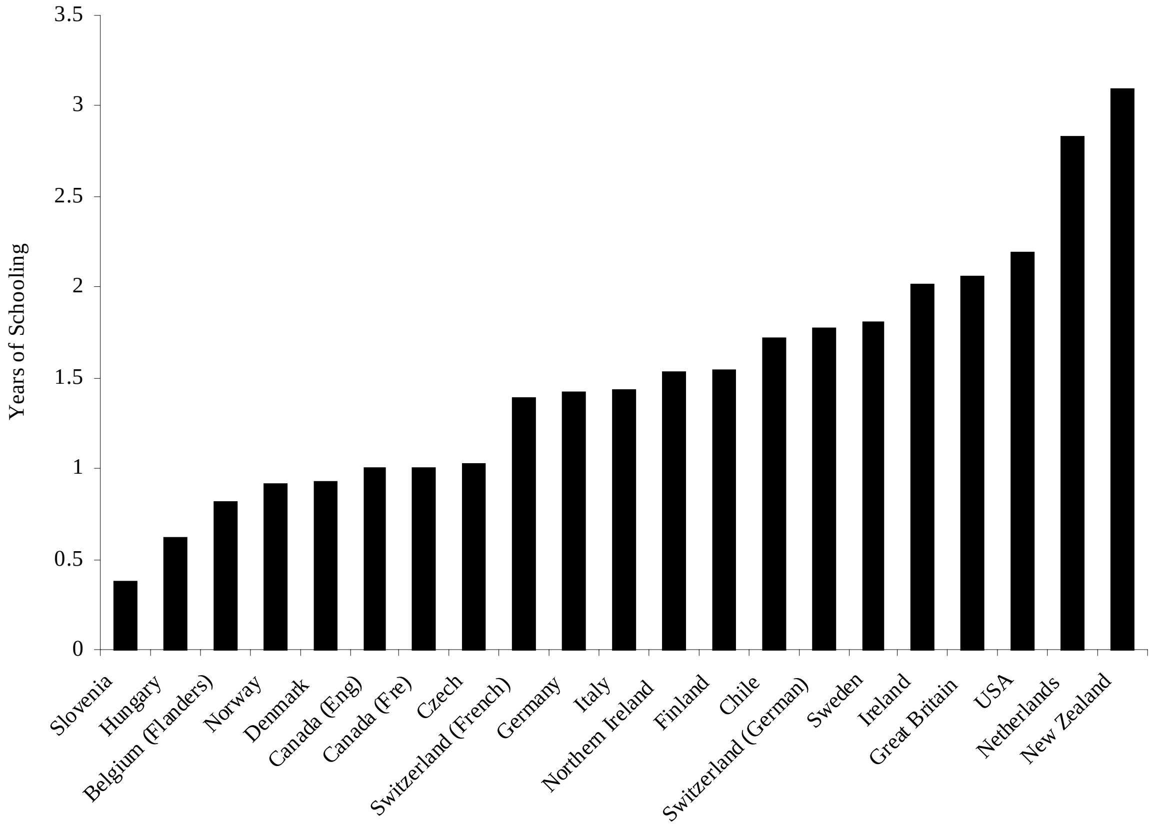


FIGURE 2 RATES OF RETURN TO ABILITY (normalised)



Note: This figure shows β_{AN} from Table 2

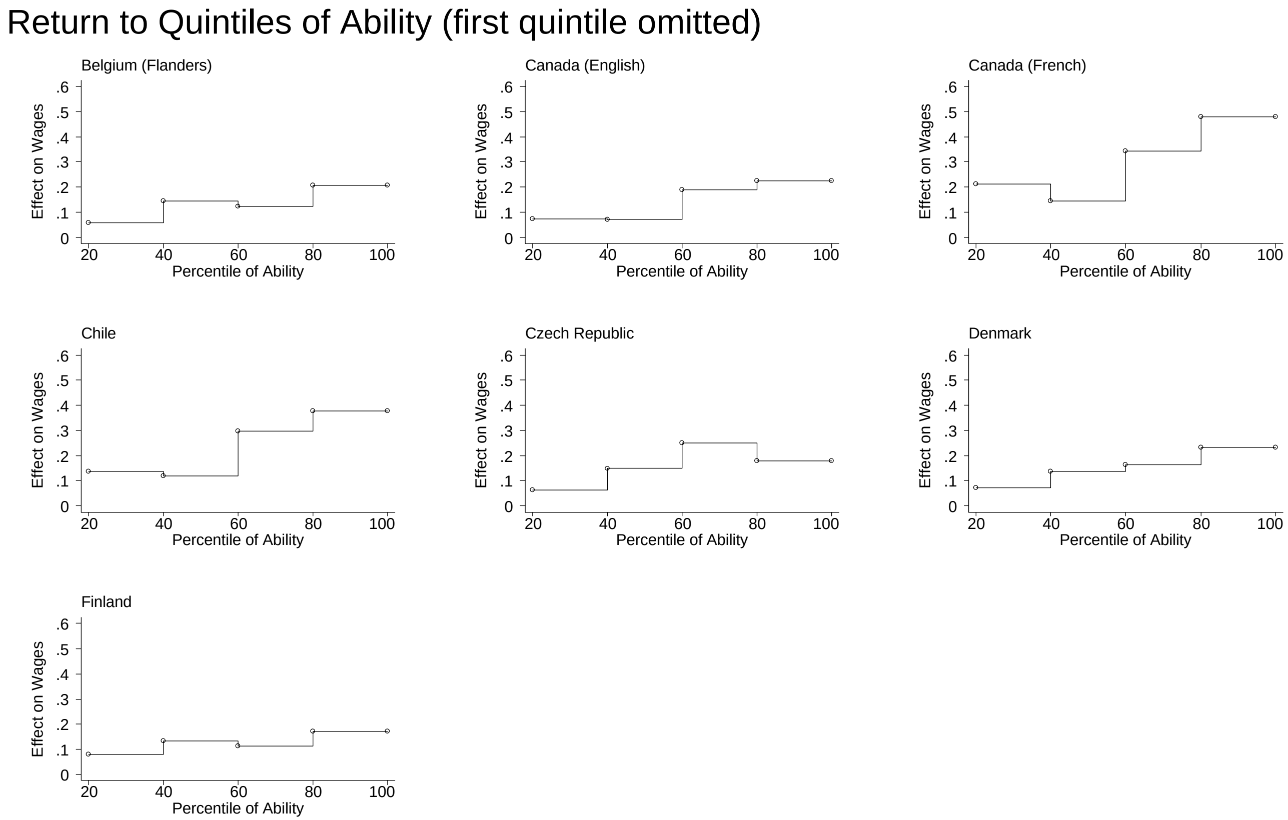
FIGURE 3 YEARS OF SCHOOLING EQUIVALENT TO MOVE FROM 25^{TH} TO 50^{TH} PERCENTILE



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 50^{th} and 25^{th} percentile of the ability 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



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

Figure 4 (cont.)

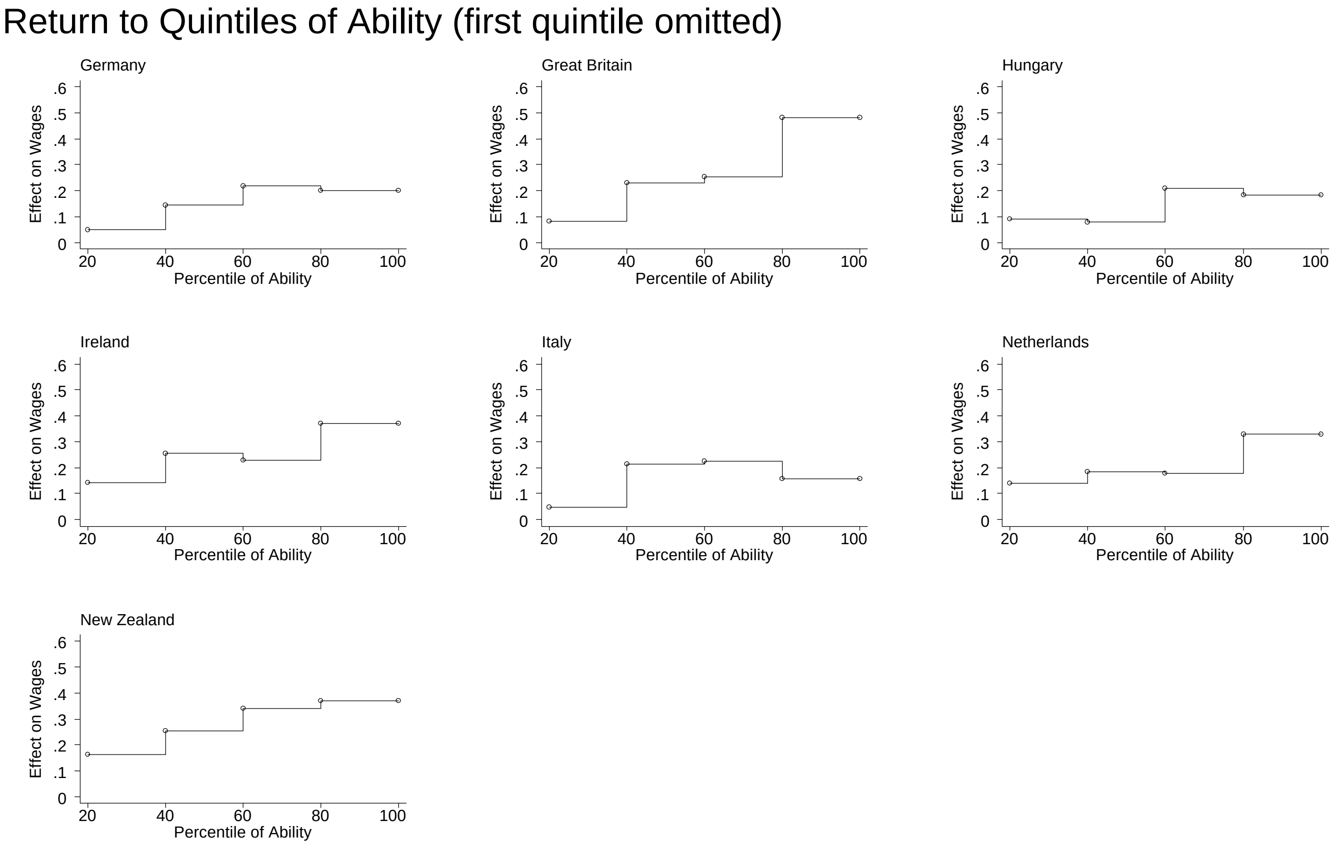


Figure 4 (cont.)