Literacy and Earnings:
An Investigation of the Interaction of Cognitive and Unobserved Skills in Earnings Generation*

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Abstract

This paper uses direct measures of literacy to examine the influence of cognitive and unobserved skills on earnings. We find that cognitive skills contribute significantly to earnings and that their inclusion in earnings equations reduces the measured impact of schooling. The impact of literacy on earnings does not vary across quantiles of the earnings distribution; schooling and literacy do not interact in influencing earnings; and introducing literacy has little effect on the estimated impact of experience. Our findings suggest that cognitive and unobserved skills are both productive but that having more of one skill does not enhance the other's productivity.

Keywords: literacy, earnings, cognitive skills, non-cognitive skills, education, ability
JEL codes: J24, J31

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I. Introduction

The statement that developed countries are experiencing a fundamental technological change has acquired the status of accepted fact. The precise nature of the shift varies from description to description but all have in common the claim that newer technologies and forms of organization favour more skilled over less skilled workers (Katz and Autor, 1999). Typically, the skills regarded as being useful in interacting with new technologies seem to be cognitive. However, a long line of work argues that non-cognitive traits explain more of earnings variation than do cognitive skills (Bowles et al, 2001). Understanding which attributes have market value requires an investigation into the importance of various skills and how they interact in influencing earnings. This paper adds to the literature that introduces skill and ability measures into earnings equations to analyse the importance of cognitive and non-cognitive attributes. Our main contribution is to go beyond such studies to examine interactions between the skills measured in literacy tests and other, usually unobserved, attributes.

The key to our investigation is data containing a direct measure of literacy skills: the Canadian component of the International Adult Literacy Survey (IALS). The IALS contains standard labour force information along with scores from a literacy test. We argue that the survey design means that the scores capture literacy skills rather than abilities. Such data provide an opportunity to identify features of earnings determination that are typically only indirectly observed. To see this, consider a hedonic model with a set of productive attributes that generate earnings. Individual earnings are a function of the value placed by the labour market on each attribute and the quantities of skills possessed by the individual. Typically, we cannot observe the skills themselves, but only inputs to their production, such as educational attainment. Regression of earnings on these skill inputs then generates coefficients that reflect both the skill production functions and the way the skills are valued. However, if we can directly observe one or more skills, as is the case here, we can learn much about how that skill is produced and how it interacts with unobserved skills in earnings generation.

Our approach is to implement quantile earnings regressions with and without literacy variables and then to use a hedonic earnings framework to relate estimates to statements about how skills interact. One key finding is that literacy has a large positive impact on earnings and its inclusion reduces the effect of schooling on earnings by about 30% at the median. We also find that: the impact of literacy on earnings does not vary across quantiles of the earnings distribution; the schooling-literacy interaction coefficient is near zero; the experience-literacy interaction coefficient is negative; and when literacy is introduced into an earnings equation the impact of experience on earnings changes very little. We find that schooling is of paramount importance in producing literacy skills while experience has no effect.

These results support a model in which cognitive skills interact with attributes created through experience in generating earnings but do not interact with other, potentially non-cognitive, skills. Further, experience does not help generate cognitive skills and whatever it does help generate is a substitute for cognitive skills in earnings generation. Our findings suggest that investment in formal schooling is necessary for producing cognitive skills: they are not obtained as a by-product of work experience. At the same time, generating more cognitive skills will not enhance the impact of other, including non-cognitive, skills. Thus, policies that increase cognitive skills are not "silver bullets" that also enhance the productivity of other skills. Issues relating to cognitive skills and other earnings-related skills can be considered separately.

The paper is organized as follows. The next section sets out an interpretative framework and our estimating equations. Section 3 describes the data and section 4 presents the quantile earnings regressions. The fifth section interprets the regression results. Section 6 relates our findings to previous research. Section 7 concludes.

II. Interpretative Framework

This section sets out a simple framework linking worker skills and earnings. This framework is used to derive our estimating equations and to interpret the results. We distinguish between attributes or skills (personal characteristics that can be acquired and enhance individual earnings) and abilities (innate productive characteristics).[1]

Assume, for the moment, workers can possess three skills in varying amounts. We begin with three skills because this is the minimum required to capture the patterns in the data. Individual earnings are a function of the skills an individual possesses and puts into use:

$$1)\quad E_i = f\ (G_{1i},\ G_{2i},\ G_{3i}) + \varepsilon_i$$

where E_i are earnings for individual i, G_{ki} is the amount of skill k that person i sells in the market, and ε_i is a disturbance term that is independent of skills. The disturbance term captures idiosyncratic events or measurement error in earnings. The earnings generation function could be interpreted as being derived from marginal product conditions related to a production function that is separable in other (non-skill) inputs or, at least in part, as representing worker capacities to capture rents from firms (Bowles et al, 2001). In the latter case, the f(.) function might vary by union status and region, though we will not consider these generalizations here. In any case, by characterizing the f(.) function, we can learn about the importance of the various skills and how they interact in earnings generation. To help focus ideas, we will think of G^1 as cognitive skills of the type measured in literacy tests, G^2 as other skills not captured in such tests, and G^3 as non-cognitive characteristics such as persistence.

It will prove easier to work with a more specific form. We find that the data is well characterized by second order polynomials in observable variables. Thus we rewrite 1) as:[2]

$$1')\ E_i = \gamma_0 + \gamma_{11}\ G_{1i} + \gamma_{21}\ G_{2i} + \gamma_{31}\ G_{3i} + \gamma_{12}\ G_{1i}^2 + \gamma_{22}\ G_{2i}^2 + \gamma_{32}\ G_{3i}^2$$
$$+ \delta_{12}\ G_{1i}\ G_{2i} + \delta_{13}\ G_{1i}\ G_{3i} + \delta_{23}\ G_{2i}\ G_{3i} + \varepsilon_i$$

Estimates of the γ and δ parameters will tell us the contribution of various skills to earnings and whether the skills are complements or substitutes in generating earnings.

Characterizing f(.) would be relatively straightforward if we observed the skills, G_{ki}. Typically, however, we only observe the inputs to skill production functions represented as:

2) $G_{ki} = h_k\ (yrs_i,\ exp_i,\ \theta_{ki})$

where *k* indexes the skill, *yrs* corresponds to years of schooling, *exp* is years of work experience and θ_k is an ability specific to the production of the *k*th skill.[3] Of course, an *h* function could be constructed such that a skill corresponds one for one with an ability. Note that we assume both that skills do not directly produce other skills and that abilities are specific to the production of particular skills. We discuss these assumptions below.

As before, discussion is simplified by considering a quadratic version:

$$2')\ G_{ki} = \alpha_{ky1}\, yrs_i + \alpha_{ky2}\, yrs_i^2 + \alpha_{ke1}\, exp_i + \alpha_{ke2}\, exp_i^2 + \alpha_{k\theta 1}\, \theta_{ki} + \alpha_{k\theta 2}\, \theta_i^2 + \alpha_{kye}\, yrs_i * exp_i + \alpha_{ky\theta}\, yrs_i * \theta_{ki} + \alpha_{ke\theta}\, exp_i * \theta_{ki}$$

where, the e, y and θ subscripts on the α's correspond to experience, years of schooling and ability, respectively.

If skills are not observed, we obtain an estimating equation by substituting equation 2) into 1). This yields a reduced form specification for earnings as a function of schooling and experience. The ability variables are unobserved and included in the error term. Inspection of equations 1') and 2') shows that the coefficients in the reduced form earnings equation will consist of a combination of γ, δ and α parameters. For example, the years-of-schooling coefficient becomes:

$$3)\ \gamma_{11}\ (\alpha_{1y1} + \alpha_{1y\theta}\ \theta_{1i}) + \gamma_{21}\ (\alpha_{2y1} + \alpha_{2y\theta}\ \theta_{2i}) + \gamma_{31}\ (\alpha_{3y1} + \alpha_{3y\theta}\ \theta_{3i}) + \delta_{12}\ (\alpha_{2y1}\ \alpha_{1y\theta}\ \theta_{1i} + \alpha_{1y1}\ \alpha_{2y\theta}\ \theta_{2i}) + \delta_{13}\ (\alpha_{3y1}\ \alpha_{1y\theta}\ \theta_{1i} + \alpha_{1y1}\ \alpha_{3y\theta}\ \theta_{3i})$$

There are several points to note from this representative expression. First, with only reduced form coefficients to work with, we cannot, in general, infer how skills are generated or how they combine to influence earnings. Second, the coefficient on a covariate such as schooling reflects the combination of how that covariate contributes to production of each skill and how those skills contribute to earnings. Third, the coefficient is a function of unobserved abilities

(θ's). This means that some type of random coefficients estimator is appropriate. We use quantile regression because it provides an appropriate estimation approach that accommodates potential variation in returns to observable variables across different values of unobservable variables.

To see the value of quantile regression in this context, consider a non-parametric approach in which one divides the data into cells defined by education and experience. For each cell one could then calculate percentiles of the earnings distribution. Quantile regression reveals how the percentiles of those distributions change as we move from lower education cells to higher education cells. Now consider a model with a single type of ability that is monotonically related to earnings. In this situation, those with higher earnings in a given cell (i.e., those at a higher quantile conditional on education and experience) possess higher ability. Then, estimated education coefficients at different quantiles would correspond to returns to education for individuals with different levels of ability. These differences in returns tell us how ability and schooling interact in earnings generation. If no coefficients, apart from the intercept, vary across quantiles then we have a pure location model, which means the distributions of earnings, conditional on schooling and experience, are identical.

We are interested in what can be learned about the structure of the earnings and skill production functions when we observe one of the skills. Labelling the observed skill G_1, we obtain a quasi-reduced form earnings regression that includes the literacy score, experience and schooling. As before, the returns to the observable variables potentially vary with unobserved abilities and, thus, quantile regression is an appropriate estimation approach.

Our estimating equation corresponding to the quasi-reduced form function including G_1 is of the form [4]:

$$\text{4)}\quad E_i = [\beta_{0j} + \beta_{1j}\ \mathrm{yrs}_i + \beta_{2j}\ \mathrm{yrs}_i^2 + \beta_{3j}\ exp_i + \beta_{4j}\ exp_i^2 + \beta_{5j}\ \mathrm{yrs}_i * exp_i$$
$$+ \beta_{6j}\ G_{1i} + \beta_{7j}\ G_{1i}^2 + \beta_{8j}\ G_{1i} * \mathrm{yrs}_i + \beta_{9j}\ G_{1i} * exp_i + \omega_j\ \mathrm{pedn}_i] + v_{ij}$$

where j indexes the quantile, G_{1i} corresponds to our measure of literacy, $pedn_i$ is a vector of parental education variables, the β's are scalar parameters, ω is a parameter vector, u is an error term, and the term in square brackets is the jth conditional quantile of earnings. Notice that the parameters are allowed to vary across quantiles to capture interactions between unobserved ability terms and observables.

III. Data

We use the IALS, an innovative survey carried out in several countries during 1994-98. The IALS includes standard questions on demographics and labour force behaviour, but also measures literacy in three domains: Prose, Document and Quantitative. Perhaps most important, IALS did not just measure abilities in mathematics and reading but assessed capabilities in applying skills to everyday activities. Thus, Prose questions assess skills ranging from identifying recommended dosages from instructions on an aspirin bottle to using "an announcement from a personnel department to answer a question that uses different phrasing from that used in the text." Document questions assess capabilities to locate and use information in various forms, and range from identifying percentages in categories in a graph to assessing an average price by combining several pieces of information. The Quantitative component ranges from simple addition of information on an order form to calculating the percentage of fat-based calories in a Big Mac based on a nutritional table. Thus, the questions are related to problem-solving and implementation of skills in daily activities and are intended not just to elicit abilities in answering current questions but adaptability to other contexts (Statistics Canada, 1996). This point is important for the interpretation of our results. We emphasize that these skills are essentially cognitive in nature.

Our data comes from the 1994 Canadian IALS that sampled 5660 individuals over age 16. We are interested in characterizing earnings in post-schooling, pre-retirement employment since jobs taken while in school or after retirement may not make full use of individuals' skills.

Thus we exclude students, the retired, and those who didn't work during the previous year. We also eliminated observations without reported earnings or years of education. Our earnings measure is annual earnings because survey questions about weeks and hours worked did not refer to the same period as the earnings question. Thus, we had no confidence in constructed weekly or hourly wages. However, our framework relates to skill prices so we prefer an earnings measure that does not reflect variation in hours of work. For that reason, we restrict our sample to full-year/full-time non-self-employed workers. Finally, we focus only on males since measuring experience is problematic for females. This leaves a sample of 646 FYFT male paid workers. To ensure results are representative of employed men, all estimates use the sample weights.

In preliminary analysis we worked with the Document, Prose and Quantitative test scores separately in hopes of identifying the impacts of different cognitive skills. However, we found strong collinearity among them and were unable to estimate separate effects for the three skill types.[5] Further, a principal components analysis indicated that the first principal component of the three test scores placed equal weight on all three and accounted for over 93% of the variance. Thus, a simple average of the three scores captures much of the information available and this is what we use in the estimations reported here.

Descriptive statistics are reported in our working paper (Green and Riddell, 2002). The literacy score (measured on a 0 to 500 scale) has a mean of 297, and a range of 72 to 443.

One shortcoming of the data is the lack of useful instruments to address potential biases arising from correlations between G_{1i} and yrs_i and unobserved ability. In Green and Riddell (2002), we discuss the merits of potential instruments. We decided it was preferable not to use instruments rather than to force results out of bad ones. Later we discuss the conditions under which our estimates can be interpreted as providing information on causal relationships.

IV. Estimation Results

We begin by estimating quantile regressions at the 10th, 25th, 50th, 75th and 90th percentiles. The goal is to implement standard human capital earnings equations, examining how results change when we introduce literacy skills.

We first regressed log annual earnings on a quadratic in years of schooling, a quadratic in experience (age - years of schooling - 6), the interaction between schooling and experience, and dummy variables for parental education.[67] Apart from inclusion of parental education, our specification is very similar to that in Buchinsky's (1997) investigation of US male earnings.

Given the squared and interaction terms in this specification, the size of the crucial schooling and experience derivatives are difficult to see from the regression results. Rather than showing the estimated coefficients (which are reported in Green and Riddell, 2002), Table 1 presents estimates of these derivatives evaluated at various experience and schooling levels. One point worth noting about the underlying coefficient estimates is that a test of whether the earnings distribution can be described with a pure location model (i.e., of the restrictions that the coefficient vector, apart from the intercept, is constant across quantiles) resoundingly rejects the associated restrictions.[8]

The results in Table 1 show that schooling impacts are lower at higher schooling levels, which reflects negative schooling squared terms in the underlying coefficients. At low experience levels, we find an inverted U-shaped pattern in the schooling derivatives, with lower derivatives at the 10th and 25th percentiles, considerably higher derivatives at the 50th and 75th derivatives, and lower derivatives again at the 90th percentile. The pattern at higher experience levels varies with education reflecting a negative schooling-experience interaction term in the underlying regressions. For men with 12 years of education and 25 years of experience, the schooling derivative is quite constant across quantiles up to the 75th percentile but is lower at the 90th percentile. For men with 16 years of schooling, the derivative declines continuously across quantiles, reaching a value that is both economically and statistically insignificant at the 90th percentile. Finally, the magnitudes of the estimates are similar to those in the previous literature. For example, Buchinsky (1997) finds a schooling derivative of .136 at the 50^{th} percentile for males with 12 years of schooling and 5 years of experience. The estimates obtained at the median are also similar to those found in the large literature using mean regression techniques. The similarity to earlier results indicates that our sample is not unusual and, so, can be used as a basis for reinterpreting results from studies that do not include literacy.

Previous authors have also found heterogeneity in returns to education across the earnings distribution. Buchinsky(1997) finds returns to education that rise across quantiles for all experience groups. Arias et al. (2001) estimate similar quantile regressions using US twins data and incorporating approaches to address endogeneity. With non-IV estimation, they find that the coefficient on education rises from the 10^{th} to the 50^{th} percentile but does not change across the upper portion of the distribution. When using instruments to address measurement error and twins status to address ability bias, their estimated schooling coefficients appear relatively similar across the distribution but are not very precisely estimated in the tails.

The estimated returns to experience are also reasonable. In general, these are declining in experience and are lower in the upper half of the distribution.

We now turn to the effects of introducing literacy. Table 2 presents results from median regressions using various specifications incorporating literacy controls. We estimated similar specifications at all 5 quantile values. Although not reported to conserve space, all those investigations lead to the same conclusions. Column 1 contains the results at the median using the specification underlying Table 1. In column 2, we introduce the literacy score.[9] Adding this variable leads to a reduction in the derivative of log earnings with respect to education. The derivative (evaluated at 12 years of schooling and 15 years of experience) falls from .102 in the first column specification to .066 when the literacy variable is included: a reduction of 36%. This suggests both that literacy skills play an important role in the returns to education and that education has a substantial impact on earnings beyond the impact related to production of literacy skills. In contrast, the coefficients on experience variables are virtually unchanged when literacy is introduced. Finally, the direct impact of literacy skills on earnings is substantial. A 20-point increase in the average literacy score (the equivalent of about 1/3 of a standard deviation in the literacy score distribution) has an impact equivalent to approximately an extra year of schooling.

The third column introduces interactions of literacy skills with experience and schooling. Key results are: the interaction of schooling and literacy is statistically insignificant; the interaction of experience and literacy is small but statistically significant; and the interaction of schooling and experience essentially falls to zero and is not significant. This latter change suggests that the significant interaction of schooling and experience in earlier specifications is actually picking up the interaction of literacy skills and experience.[10] Column 4 contains our preferred specification, which includes the interaction of the literacy score with experience but drops the other (insignificant) interactions. In this specification, the schooling derivative evaluated at 12 years of education is .070 while the literacy score derivative evaluated at 15 years of experience is .003. Again, the literacy effect is substantial.

Table 3 reports results from quantile regressions using our preferred specification. Here one can see that results are broadly comparable across quantiles. Table 4 contains schooling, experience and literacy score derivatives similar to those in Table1. Comparing the schooling derivatives in Table 4 to those evaluated at 15 years of experience (a middle value) in Table 1 shows that introducing literacy generates much larger declines in the schooling derivative at the top of the earnings distribution than the bottom. In particular, the schooling derivative (at 12 years of schooling and 15 years of experience) falls by 21% at the 10th percentile but by 58% at the 90th percentile. The schooling derivative at the 90th percentile for workers with 16 years experience falls to zero once literacy skills are included. At 12 years of schooling, the net impact of introducing literacy is a set of schooling derivatives that are nearly constant up to the 75th percentile and then decline in the upper tail of the distribution. In terms of experience, the derivatives reported at 15 years of experience in Table 4 are very similar to those for 15 years of experience and 12 years of education in Table 1. Thus, introducing literacy changes the experience derivatives very little. Perhaps the most interesting result in Table 4 is that the derivatives with respect to the literacy score are remarkably similar across quantiles. This is not surprising once one examines the coefficients on the literacy score and literacy-experience interaction in Table 3. Both sets of coefficients are very similar across quantiles. A test of whether these two sets of coefficients are constant across quantiles does not reject the null hypothesis at conventional significance levels.[11] The experience derivatives also exhibit considerable similarity across quantiles, though not as strong as the literacy derivatives. A test for whether the coefficients on experience, experience squared and the experience-literacy score interaction do not change across quantiles fails to reject the restriction of constancy.[12]

In Green and Riddell (2002) we also present results from a mean regression of the literacy score on observed inputs to skill production: schooling, experience, and parental education. The key results are that years of education play a very strong role in determining literacy, though that is tempered by a strong negative quadratic term coefficient. Parental education plays some role in determining literacy, though not a particularly strong or statistically well-defined role. This fits with Charette and Meng(1998)'s finding, using an earlier Canadian literacy survey, that impacts of family background on literacy fade to unimportance once education is included in a regression. Finally, the effects of experience are both economically insubstantial and statistically insignificant. It appears that literacy is generated from formal schooling, and to some extent parental input, but not from labour market experience. This implies that whatever skills are acquired through experience, they are not the type of cognitive skills captured even on a literacy test that focuses on capabilities in everyday tasks.

V. Interpreting the Earnings Regression Results

In this section, we use the estimation results to put restrictions on the functions in equations 1) and 2). Being able to observe one of the attributes allows us to make statements not only about its relation to earnings but also about how other attributes are generated and how they interact in influencing earnings. We will put the discussion in terms of the parameters in 1') and 2') but the conclusions apply to more general functions. Moving through our results sequentially we find the following.

i) The coefficients on G_{1i} are large and statistically significant. This means γ_{11} is non-zero, i.e., cognitive skills directly determine earnings.

ii) The coefficients on G_{1i}^2 are not significant. This implies $\gamma_{12} = 0$.

iii) Even after controlling for literacy, the parameters related to schooling and schooling squared are large and statistically significant. This result means that G_{2i} and/or G_{3i} influence earnings (i.e., some combination of γ_{21}, γ_{22}, γ_{31} and γ_{32} are non-zero) and that schooling helps produce these skills (i.e., some combination of (α_{ky1}, α_{ky2}, and $\alpha_{ky\theta}$ k=2,3, are non-zero).

iv) Even after controlling for G_{1i}, the parameters related to experience and experience squared are large and statistically significantly. This implies that G_{2i} and/or G_{3i} generate earnings and that experience is an input into producing these skills (i.e., some combination of α_{ke1}, α_{ke2}, and $\alpha_{ke\theta}$, k=2,3, are non-zero).

v) The coefficients on the literacy-experience interaction are significantly different from zero. This means that δ_{12} and/or δ_{13} does not equal zero and that whichever is non-zero corresponds to the interaction of G_{1i} and a skill that is produced at least partly with experience. For example, if $\delta_{12}\neq 0$ then G_{2i} is produced in part with experience.

vi) The coefficients on the literacy-schooling interaction are small and insignificant. This could arise if schooling does not produce any other skill. But, as discussed above, schooling does help produce at least one other skill. For the literacy-schooling interaction to be zero in that situation, literacy and the skill produced using schooling must not interact in earnings generation. For example, if schooling helps produce G_{3i} then δ_{13}=0. From v) we know that we need one skill (which we will arbitrarily call G_{2i}) that is a function of experience and that interacts with G_{1i} in earnings generation ($\delta_{12}\neq 0$). But with $\delta_{12}\neq 0$, G_{2i} must not be produced using schooling - otherwise the interactions of G_{1i} and schooling would be non-zero. Thus, for all of these results to hold, we require at least two skills in addition to G_{1i}: G_{2i} which is a function of experience but not of schooling and which interacts with G_{1i}; and G_{3i} which is produced with schooling and does not interact with G_{1i}. Note G_{3i} may be a function of experience. These arguments imply: $\delta_{12}\neq 0$, $\delta_{13}=0$, $\alpha_{2y1}= \alpha_{2y2} = \alpha_{2y\theta} = 0$, some combination of α_{2e1}, α_{2e2}, and $\alpha_{2e\theta}$ are not zero, and some combination of α_{2y1}, α_{2y2} and $\alpha_{2y\theta}$ are not zero.

vii) The coefficients on the schooling-experience interaction are small and insignificant. This implies that schooling and experience must not interact in producing G_{2i} and G_{3i}, i.e., $\alpha_{2ey} = \alpha_{3ey} = 0$. It also means that there cannot be a higher order term in G_{3i}, since such a term would imply an interaction between schooling and experience (thus, $\gamma_{32} = 0$). Further, since we have shown that G_{2i} is a function of experience and G_{3i} is a function of schooling, the lack of a schooling-experience interaction implies that G_{2i} and G_{3i} do not interact (i.e, $\delta_{23} = 0$).

viii) The fact that the derivative of earnings with respect to literacy does not vary across quantiles implies that G_{1i} does not interact with an unobserved ability, θ, in generating earnings. This has several implications. First, it means that G_{2i} is not produced using θ because G_{1i} and G_{2i} interact in earnings generation. Second, G_{3i} may be produced using an unobserved θ, since G_{1i} does not interact with G_{3i}. Thus, G_{1i} only interacts with a skill that is generated solely by experience. It does not interact with unobserved ability or skills that derive from unobserved ability. This means that cognitive skills do not enhance returns to other skills or vice versa. They are substitutes for skills created purely from experience but that is their only interaction.

ix) The experience derivatives are also constant across quantiles. This cannot further restrict how

G_{2i} is produced since it depends only on experience. However, it does place restrictions on production of G_{3i}. In particular, experience and unobserved ability must not interact in the production of G_{3i}.

x) Estimates from regressing literacy on potential determinants show that schooling is an important input. On the other hand, G_{1i} is not produced using experience.[13]

Taking all of these points and applying them to equations 1') and 2'), we arrive at an implied set of earnings and attribute generation functions that are consistent with the reduced form patterns in the data::

$$5)\ E_i = \gamma_0 + \gamma_{11}\ G_{1i} + \gamma_{21}\ G_{2i} + \gamma_{31}\ G_{3i} + \gamma_{22}\ G_{2i}^2 + \delta_{12}\ G_{1i}\ G_{2i} + \varepsilon_i$$

$$6a)\ G_{1i} = \alpha_{1y1}\, yrs_i + \alpha_{1y2}\, yrs_i^2 + \alpha_{1\theta 1}\, \theta_{1i} + \alpha_{1\theta 2}\, \theta_{1i}^2 + \alpha_{1y\theta}\, yrs_i * \theta_{1i}$$

$$6b)\ G_{2i} = \alpha_{2e1}\, exp_i + \alpha_{2e2}\, exp_i^2$$

$$6c)\ G_{3i} = \alpha_{3y1}\, yrs_i + \alpha_{3y2}\, yrs_i^2 + \alpha_{3e1}\, exp_i + \alpha_{3e2}\, exp_i^2 + \alpha_{3\theta 1}\, \theta_{3i} + \alpha_{3\theta 2}\, \theta_{3i}^2 + \alpha_{3y\theta}\, yrs_i * \theta_{3i}$$

or, stating the earnings generation function more generally:

$$7)\ E_i = f_a\ (G_{1i}(yrs_i, \theta_{1i}),\ \ G_{2i}(exp_i)) + f_b(G_{3i}(h_{3a}(yrs_i,\ \ \theta_{3i})\ +\ h_{3b}(exp_i)) + \varepsilon_i$$

where the expression for G_{3i} denotes that to the extent that experience enters the production of G_{3i}, it must do so in an additively separable manner relative to ability and schooling. Equation 7) is the most parsimonious specification consistent with the reduced form patterns revealed in the quantile regressions. Thus, we argue that one needs at least three skills to capture the observed patterns. There may be more than three relevant skills but even in that case, one still needs a specification in which G_{1i} and G_{2i} are separable from other skills. Further, the other skills need to be separable functions of experience. Thus, one can interpret $f_b(\ )$ as representing the contribution of all skills other than literacy and a skill generated solely from experience.

Equation 7) points to several interesting conclusions. Most importantly, it says that with the exception of one attribute generated solely from experience, cognitive skills do not interact with other attributes in earnings generation. Other attributes such as beauty (Hamermesh and Biddle, 1994) and leadership skills (Kuhn and Weinberger, 2000) may influence earnings but their contributions are not enhanced by additional literacy. Literacy skills are not a silver bullet that contribute directly to earnings and increase returns to other attributes.

The results also indicate that literacy skills are generated with schooling not experience. Thus, policies aimed at improving cognitive skills should focus on formal schooling. Policies designed to increase work experience can lead to earnings growth but they will not lead to greater cognitive skills in the workforce. More generally, the results imply a need for separate approaches for generating various skills: schooling is needed for cognitive skills; experience alone is an input into one attribute; and whatever creates the remaining attributes does not enhance returns to either the experience-based attribute or cognitive skills.

The results suggest an interesting and complicated role for experience. Experience does not help generate literacy and does not interact substantially with the non-cognitive abilities that remain in the error term after controlling for G_{1i}, but it does interact with G_{1i} in production. Given the negative interaction between experience and literacy, experience generates a skill that is a substitute for the cognitive skills measured in the literacy test. This might arise if cognitive skills are important early in the career but that as an individual builds experience, the specific skills generated on the job become more important.

Several points about the model specification deserve further discussion. First, with no credible instruments, it is worth discussing the conditions under which our estimates provide the basis for valid causal conclusions. The key to these conditions, of course, rests in the error term. The error term in equation 7) includes only θ_{3i} and ε_i. We assume that ε_i represents only measurement error in earnings and is independent of other observable variables. Note that cognitive ability, θ_{1i}, is not in the error term because it is assumed to contribute only to G_{1i}, which is included in the regression. The key assumption required for a causal interpretation is that both G_{1i} and yrs_i are uncorrelated with θ_{3i}, which we interpret as non-cognitive abilities.

Is it plausible that cognitive skills and schooling are uncorrelated with θ_{3i}? In a standard school choice model (Card, 1999), years of schooling and unobserved abilities would generally be correlated if returns to schooling vary with ability. In our case, our estimates indicate that returns to schooling vary across quantiles (though not to a great extent), suggesting that there is variation in returns to schooling with ability. Thus, for schooling to be uncorrelated with ability, we require that returns to schooling may vary with ability but that individuals do not make their schooling choices based on that variation. This would be the case if individuals either do not know their own ability or do not know how their ability alters the market value of schooling. This assumption becomes somewhat more plausible if one assumes that θ_{1i} contributes only to production of G_{1i} and thus is not in the error term when we control for G_{1i}. In that case, we are only requiring that individuals do not know (and therefore do not act upon) how non-cognitive abilities such as beauty alter returns to schooling.

For literacy to be uncorrelated with the error term we need the same conditions as those required for schooling to be uncorrelated, since G_{1i} is a function of schooling, plus the requirement that θ_{1i}, the other main determinant of literacy skills, is uncorrelated with the error term. This is the reason for our assumption that only G_{1i} is a function of θ_{1i} , since if other attributes are produced using cognitive abilities then θ_{1i} would be in the error term even conditioning on G_{1i} and endogeneity would definitely exist. However, we also require the assumption that θ_{1i} and θ_{3i} are uncorrelated, i.e., that that non-cognitive abilities, such as beauty or leadership skills, are uncorrelated with cognitive abilities. This assumption does not seem overly strong. Overall, the set of assumption required to allow causal interpretation of our estimates is clearly very stringent, but does not appear to be completely beyond credibility.

Our specification is based on the assumption that any one skill is not directly used in producing any other skill. If G_{1i} helps produce other skills, our results could bear a different interpretation. For example, the negative literacy-experience interaction could reflect their being substitutes in the production of G_{2i} rather than G_{1i} and G_{2i} being substitutes in earnings generation. Changing the framework in this way would not alter the main conclusions (particularly that literacy does not alter returns to unobserved skills) unless effects of literacy in producing other skills directly offset their effects in interacting with other skills in earnings generation. The more parsimonious conclusion we have drawn here seems to be more reasonable but we cannot formally reject either possibility.

The result that literacy returns are constant across quantiles is striking. The robustness of this result was checked in numerous specifications not reported here. Removing the parental education variables and/or introducing higher order terms in experience and literacy as well as interactions between literacy and schooling do not change our conclusions. When the interaction between schooling and experience is reintroduced, even though it is generally insignificant, the literacy coefficients appear more erratic across the quantiles. However, we still cannot reject the restrictions that the coefficients on literacy and the experience-literacy interaction are constant across quantiles. Another robustness concern is with the measurement of literacy. We have used the literacy score as if it were cardinally meaningful. To the extent this is not true, one would expect to see non-linearities in the relationship between literacy and earnings (e.g., if a person with twice the literacy score has less than twice the literacy skills that employers value then the relationship between earnings and literacy should be concave). However, we find no evidence of non-linearities in this relationship. Further, even if the literacy score were only ordinally meaningful, this would probably not change the interpretations we have given to the fact that the literacy coefficient does not vary across quantiles.

To put the argument more precisely, assume that there is a cardinally meaningful cognitive skill index, G_{1i}*, and that the measured literacy score is related to it through a monotonic function, $G_{1i} = \mu(G_{1i}*)$. For simplicity, write earnings as

$$8)\quad E_i = [\phi_{0j} + \phi_{1j}\ G_{1i}] + u_{ij}$$

and the literacy coefficients as

$$9)\quad \phi_{1j} = \phi_1 + \omega\ \theta_j$$

where the term in square brackets in 8) is the jth conditional quantile and θ_j is the value of an unobserved variable which defines the jth quantile conditional on G_{1i}. We assume the form in 9) for simplicity but our conclusions hold if we allow φ_{1j} to be a more general function of θ_j. Now replace G_{1i} with the equivalent nonlinear function of G_{1i}*, thus expressing earnings in terms of the true skill index. We then get

$$10)\quad E_i = [\phi_{0j} + \phi_{1j}\ \mu\ (G_{1i}*)] + u_{ij}$$

Now, if we test for whether the coefficient on G_{1i} varies across quantiles in equation 8) and find that it does not (i.e. that $\omega = 0$) then the coefficients on both linear and any higher order terms in G_{1i}* will also not vary across quantiles as long as the $\mu(.)$ function is not a function of θ. Since there is no reason why this transformation would be a function of θ, we conclude that our result that returns to literacy do not vary across quantiles is not sensitive to the exact transformation on true skills represented by the test score.

VI. Relationship to Earlier Studies

One key assumption is that we have a measure of cognitive skills. Readers may wonder about the relationship between results obtained when controlling for literacy and those obtained when controlling for a measure of cognitive ability, θ_{1i}. A variety of papers include variables intended to capture cognitive ability in response to potential endogeneity of schooling. Much of this work has been done in the US, using scores on the Armed Forces Qualification Test (AFQT) as a measure of ability (e.g., Griliches and Mason (1972) and Chamberlain (1977)). The AFQT includes questions on vocabulary, math and spatial relations and is intended as an IQ test adapted for the military. The goal of the test was to ascertain general cognitive abilities. In early work using AFQT scores, including the score in an earnings regression reduces the coefficient on schooling only marginally and the direct contribution of ability to earnings is "quite small" (Griliches(1977), p.9). Taken at face value, these results imply that the ability bias in measuring returns to education is quite small and that ability itself plays only a minor direct role in generating productive skills. This seems to contrast with our finding that cognitive skills play a strong role in earnings determination. We believe these differences partly reflect differences in what the variables measure. “Ability” measures are typically obtained at a time much before the period covered by the earnings data (e.g., entered the armed forces) and are intended to capture innate abilities. In contrast, IALS attempts to capture literacy skills used in everyday life that the individual possesses at the time when earnings are measured.

How do ability coefficients relate to estimates of the literacy coefficient? Recall that we view the vector of abilities as inputs into skill production rather than as productive skills in their own right. Given an observation on ability θ_{1i}, we can write the earnings derivative as:

$$11)\quad \frac{\partial E}{\partial \theta_1} = \frac{\partial f}{\partial G_1} * \frac{\partial h_1}{\partial \theta_1} + \frac{\partial f}{\partial G_2} * \frac{\partial h_2}{\partial \theta_1} + \frac{\partial f}{\partial G_3} * \frac{\partial h_3}{\partial \theta_1}$$

where the i subscript is suppressed for simplicity. The first derivative on the right hand side of 11) is the estimated coefficient on G_{1i}. Thus, the coefficient on a cognitive skill will only be the same as the coefficient on a cognitive ability if $\delta h_1/\delta\theta_1 = 1$ <u>and</u> either cognitive ability only produces cognitive skills or skills other than literacy are not productive. The first of these conditions implies that a 1% increase in cognitive ability is equivalent to a 1% increase in the person’s cognitive skill. However, if cognitive abilities are just one input into skill production then this need not be the case and we could observe, for example, a cognitive ability measure having a much smaller coefficient in an earnings regression than a cognitive skill measure.[14]

Our results are related to a growing literature on the importance of non-cognitive attributes in earnings generation recently surveyed in Bowles et. al.(2001). These authors establish a framework somewhat like ours but in a mean regression specification. They cite several studies in which including a measure of cognitive ability reduces the schooling coefficient by about 20%. This is less than the reduction we found using the IALS but the cited studies generally use ability tests such as the AFQT. In either case, though, their conclusion is that the majority of the schooling impact is through endowing individuals with non-cognitive traits such as persistence and willingness to follow orders. Further, they argue that the relatively low R^2 values obtained even in regressions that include ability measures point to the importance of other worker attributes in generating earnings. Our findings with respect to schooling derivatives, literacy effects, and small pseudo-R^2 values support this interpretation.

Heckman and Rubinstein (2001) also obtain findings that they interpret as pointing to the importance of non-cognitive skills. In particular, they find that holders of General Educational Development degrees (GED's) -- high school degrees obtained through testing by former dropouts -- earn more than other dropouts but less than high school graduates. Heckman and Rubinstein argue that this is consistent with the GED holder having more cognitive skills than other dropouts (enough to make them the functional equivalents of high school graduates) but fewer non-cognitive skills than high school graduates. This supports earlier work in Cawley et. al. (1996) that indicates that cognitive abilities are a relatively minor predictor of earnings.

The main difference between our paper and this earlier work is that we use a direct measure of cognitive skill to examine the nature of potential interactions between cognitive and other skills. While Bowles and Gintis (2000) argue that cognitive and non-cognitive abilities interact positively in earnings generation, we find that cognitive skills interact negatively with skills generated through labour market experience and not at all with other (possibly non-cognitive) skills.

More recent contributions approach the problem by introducing measures of non-cognitive attributes and abilities into earnings functions. Hamermesh and Biddle (1994) show that how a person looks can affect their earnings. Goldsmith et. al.(1997) use US data to show that the elasticity of earnings with respect to measures of self-esteem is higher than the elasticities associated with schooling. Kuhn and Weinberger (2000) show that whether an individual was a leader in high school has strong positive impacts on wage levels a decade later. Interestingly, in Kuhn and Weinberger(2000) when they move from a simple specification to one that includes the individual's percentile in math and reading tests, the reading and math scores enter significantly but the coefficients on the leadership variables show little change. This is consistent with our claim that cognitive and non-cognitive attributes are orthogonal. Overall, there is clear evidence that variables beyond those measuring cognitive skills and standard human capital variables affect earnings. Our results suggest that their impact on earnings and those of cognitive skills may be separable.

VII. Conclusion

In this paper, we use a direct measure of literacy to examine the importance of both cognitive and other skills and their interaction in generating earnings. We find that cognitive skills contribute significantly to earnings and that their inclusion in a regression leads to a reduction in the measured impact of schooling on earnings. This finding points partly to the importance of cognitive skills in earnings generation, but is also consistent with non-cognitive skills being even more important (Bowles et al, 2001). We also find that the impact of literacy on earnings does not vary across quantiles of the earnings distribution, that the interaction of schooling and literacy has a coefficient very near zero, that the interaction of experience and literacy is negative, and that introducing literacy skills into earnings regressions changes the impact of experience on earnings very little. Regressing the literacy score on various potential inputs to literacy production, we find that schooling is of paramount importance in explaining individual literacy while experience has no effect. Taken together, these results support a model in which literacy skills interact with whatever skills are created through experience in generating earnings but do not interact with other, potentially non-cognitive, skills. Thus, our findings suggest that cognitive and non-cognitive skills are both productive but that having more of one does not enhance the productivity of the other. Experience plays an interesting role in our results. We interpret our estimates as implying that experience does not help create cognitive skills of the type captured in a literacy test and does not interact with non-cognitive skills. Whatever skills are generated through experience are, however, substitutes for cognitive skills in production.

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Table 1: Derivatives of Log Earnings at Various Quantiles

	10^{th} Percentile	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile	90^{th} Percentile
Schooling Derivatives					
School = 12 Exp = 5	.087 (.028)	.085 (.017)	.13 (.017)	.15 (.011)	.098 (.032)
School = 12 Exp = 15	.080 (.024)	.078 (.012)	.10 (.011)	.11 (.0090)	.072 (.022)
School = 12 Exp = 25	.072 (.023)	.070 (.0092)	.077 (.0096)	.078 (.0084)	.046 (.014)
School = 16 Exp = 5	.069 (.020)	.055 (.0099)	.080 (.012)	.090 (.0084)	.057 (.020)
School = 16 Exp = 15	.061 (.014)	.047 (.0055)	.054 (.0063)	.055 (.0054)	.031 (.012)
School = 16 Exp = 25	.053 (.014)	.040 (.0083)	.029 (.0093)	.021 (.0049)	.0051 (.011)
Experience Derivatives					
School = 12 Exp = 5	.066 (.011)	.073 (.0075)	.069 (.0061)	.056 (.0057)	.058 (.011)
School = 12 Exp = 15	.041 (.0066)	.042 (.0043)	.042 (.0035)	.037 (.0023)	.032 (.0056)
School = 12 Exp = 25	.016 (.0031)	.011 (.0027)	.015 (.0019)	.019 (.0029)	.0057 (.0043)
School = 16 Exp = 5	.063 (.011)	.070 (.0064)	.058 (.0050)	.042 (.0053)	.047 (.0083)
School = 16 Exp = 15	.038 (.0071)	.039 (.0036)	.032 (.0036)	.024 (.0022)	.021 (.0035)
School = 16 Exp = 25	.013 (.0046)	.0083 (.0034)	.0048 (.0040)	.0049 (.0032)	-.0047 (.0046)

Note: Calculations based on coefficients reported in Green and Riddell (2002). Standard errors created from bootstrapped variance-covariance matrix for the coefficients.

Table 2: Log Annual Earnings Median Regressions

Variables	1	2	3	4
Years of Education	.27* (.042)	.21* (.040)	.22* (.044)	.18* (.037)
Years of Education Squared	-.0055* (.0012)	-.0047* (.0010)	-.0035* (.0013)	-.0046* (.0011)
Average IALS Score	-	.0029* (.00047)	.0082* (.0023)	.0057* (.00085)
Experience	.11* (.016)	.10* (.010)	.12* (.016)	.12* (.017)
Experience Squared	-.0013* (.00013)	-.0012* (.00010)	-.0011* (.00015)	-.0011* (.00016)
Years of Education *Experience	-.0024* (.00089)	-.0021* (.00057)	-.00080 (.00094)	-
Years of Education *IALS Score	-	-	-.00020 (.00014)	-
Experience *IALS Score	-	-	-.00014* (.000054)	-.00018* (.000046)
Father's Ed - High School or Post Sec.	.032 (.042)	.0058 (.045)	-.057 (.045)	-.050 (.042)
Father's Ed - University	-.22* (.096)	-.19* (.068)	-.28* (.069)	-.33* (.058)
Mother's Ed - High School or Post Sec.	.011 (.045)	-.090+ (.049)	-.043 (.044)	-.031 (.044)
Mother's Edn - University	-.042 (.17)	.028 (.12)	.12 (.12)	.14 (.10)
Constant	7.13* (.43)	7.05* (.31)	5.99* (.25)	6.65* (.35)
Pseudo R^2	.26	.30	.31	.30

Notes: * (+) corresponds to significantly different from zero at the 5%(10%) level. Standard errors generated from bootstrapped variance-covariance matrix, based on 200 replications.

Table 3: Log Annual Earnings Quantile Regressions With Literacy Variables

Variables	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile
Years of Education	.15* (.061)	.18* (.045)	.18* (.038)	.18* (.042)	.11* (.045)
Years of Education Squared	-.0038* (.0019)	-.0046* (.0014)	-.0046* (.0012)	-.0049* (.0013)	-.0033* (.0014)
Average IALS Score	.0061* (.0018)	.0063* (.00083)	.0057* (.00088)	.0059* (.00085)	.0067* (.0016)
Experience	.13* (.031)	.13* (.018)	.12* (.019)	.13* (.010)	.10* (.029)
Experience Squared	-.0013* (.00027)	-.0013* (.00017)	-.0011* (.00016)	-.0010* (.00021)	-.0010* (.00033)
Experience *IALS Score	-.00018* (.000074)	-.00017* (.000043)	-.00018* (.000049)	-.00021* (.00046)	-.00016* (.000066)
Father's Ed - H. School or Post Sec.	.13 (.11)	.024 (.10)	-.050 (.043)	-.010 (.090)	-.15* (.073)
Father's Ed - University	.14 (.13)	-.12 (.076)	-.33* (.058)	-.30* (.11)	-.26* (.10)
Mother's Ed - H. School or Post Sec.	-.27 (.11)	-.12+ (.067)	-.031 (.042)	-.093 (.081)	-.015 (.081)
Mother's Ed - University	-.44* (.18)	-.23 (.20)	.14 (.12)	.069 (.11)	.060 (.12)
Constant	6.20* (0.92)	6.13* (.51)	6.65* (.38)	6.71* (.44)	7.52* (.68)
Number of Obs.	646	646	646	646	646
Pseudo R^2	.22	.25	.26	.22	.15

Notes: * (+) corresponds to being significantly different from zero at the 5% (10%) level. Standard errors generated from bootstrapped variance-covariance matrix, based on 200 replications.

Table 4
Derivatives of Log Earnings With Respect to
Schooling, Experience and Literacy

	10^{th} Percentile	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile	90^{th} Percentile
Schooling Derivatives					
School = 12	.063 (.019)	.067 (.012)	.067 (.013)	.064 (.013)	.030 (.014)
School = 16	.039 (.012)	.029 (.0080)	.031 (.0076)	.024 (.0070)	.0058 (.010)
Experience Derivatives					
Exp = 5 Score = 287	.063 (.012)	.069 (.0065)	.060 (.0062)	.058 (.0066)	.052 (.012)
Exp = 15 Score = 287	.037 (.0069)	.040 (.0037)	.038 (.0036)	.037 (.0031)	.028 (.0059)
Exp = 25 Score = 287	.010 (.0031)	.011 (.0028)	.015 (.0027)	.017 (.0030)	.0052 (.0035)
IALS Score Derivatives					
Exp = 5	.0049 (.0014)	.0054 (.00066)	.0046 (.00069)	.046 (.00067)	.048 (.00013)
Exp = 15	.0032 (.00084)	.0035 (.00049)	.0030 (.00047)	.0026 (.00045)	.0032 (.00080)
Exp = 25	.0015 (.00070)	.0017 (.00064)	.0013 (.00067)	.00066 (.00061)	.0017 (.00067)

Note: Calculations based on coefficients reported in Table 3. Standard errors created from bootstrapped variance-covariance matrix for the coefficients.

Endnotes

1. The distinction between attributes (personal characteristics that enhance earnings) and skills (characteristics that aid productivity in specific tasks) may be important in some circumstances. In this taxonomy, skills focus on facility with specific tasks while attributes include characteristics such as persistence and willingness to follow orders. This distinction does not matter here, and we use both terms interchangeably.

2. We omit higher order interaction terms because they do not enter our specifications consistently.

3. The h(.) functions may contain other inputs (for example, we consider parental education in our empirical work). We restrict discussion to schooling and experience because additional inputs do not change the discussion but complicate the expressions.

4. These specifications represent the outcome of previous testing. In particular, further interactions among the higher order terms in schooling and experience and the other variables were found to be insignificantly different from zero. We also used specifications that included cubic and quartic terms in experience but doing so resulted in less precision without changing any conclusions.

5.The R^2 changed very little whether we included one score or all three and the standard errors on the coefficients associated with the test scores became quite large when all three scores were included. The correlation between prose and document literacy scores is .897 in our data; that between prose and quantitative is .894; and that between document and quantitative is .904.

6.Many US studies find that the partial relationship between earnings and education is approximately linear, so omit the quadratic schooling term (Card, 1999). The schooling-experience interaction term is also often omitted for similar reasons.

7. In an earlier set of estimations, we also included cubic and quartic terms in experience. None of our results or conclusions changed with their inclusion and we elected to use a more parsimonious specification given our combination of using quantile regressions on a somewhat small sample.

8. To run this test we first generated an estimate of the variance-covariance matrix for the complete set of estimated coefficients across all 5 estimated quantiles. We generated the variance-covariance matrix using what Buchinsky (1997) calls the Design Matrix Bootstrap Estimator (with 200 replications) adjusted to utilize the IALS sample weights. All subsequent testing is based on this, or similarly constructed, variance-covariance matrices. The test statistic is distributed as $\chi^2(36)$ and takes a value of 108.34. The relevant critical value for a 5% level of significance test is 50.71.

9. We also implemented specifications including higher order terms in the literacy score but

these were never significant. Osberg (2000) examines the relationship between earnings and literacy using the same data. He focuses on whether monotonic transformations of the literacy variable alter conclusions. For men, his tables indicate that such transformations do not substantially alter the estimated schooling coefficient, indicating that using the score level as we do here is appropriate.

10. We had some concern about collinearity among the interaction variables. When we ran specifications with either the interaction of experience and schooling or the interaction of schooling and literacy plus the interaction of experience and literacy, in both cases the experience-literacy score coefficient was significantly different from zero while the other interaction was small and not significantly different from zero.

11. The test statistic is distributed as $\chi^2(8)$ and takes a value of 4.96. The relevant critical value for a 5% level of significance test is 15.51 and for a 10% level of significance test is 13.36.

12. The test statistic is distributed as $\chi^2(12)$ and takes a value of 18.29. The relevant critical value for a 5% level of significance test is 21.03 and for a 10% level of significance test is 18.55.

13. These results can also be seen from the way the coefficients in the earnings regression change when moving from a specification without G_{1i} to one including G_{1i}. The fact that the coefficient on schooling declines when literacy is introduced implies that schooling must influence G_{1i} since introducing G_{1i} will reduce the coefficient on schooling by a term that represents the combination of the impact of G_{1i} on earnings (which we know to be positive and significant) and the impact of schooling on literacy. If the latter were zero, the schooling coefficient would not change when we introduce literacy. Thus, the fact that the coefficients on experience do not change with the introduction of G_{1i} implies that experience does not contribute to producing literacy.

14. Another possible source of difference between our results and those from the earlier literature is the time period. Murnane, Willett and Levy (1995) find increased returns to both an ability measure and schooling over time. However, in summarizing a range of studies examining this issue, Bowles et al.(2001) conclude that there is no evidence of an increased return to cognitive ability in the US over time. Interestingly, Murnane et al's tables show (though they do not comment on this point) that the coefficient on years of experience in their earnings regression does not change when they introduce their ability measure. This fits with our claim that experience does not help to produce whatever is being measured by these tests.