Understanding Educational Impacts: The Role of Cognitive Skills*

David A. Green
Department of Economics
University of British Columbia

W. Craig Riddell
Department of Economics
University of British Columbia

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1. Introduction

Education has numerous – and profound – consequences for individuals and society. As many studies have documented, education is one of the best predictors of "who gets ahead." Better-educated workers experience higher lifetime earnings, less unemployment and work longer. Higher education is also associated with longer life expectancy, improved health, reduced participation in crime, and greater civic participation. These correlations have been known for along time. A substantial body of recent research concludes that these relationships reflect, at least in part, causal influences of schooling on individual outcomes. The relationship between education and earnings has been extensively investigated. As the surveys by Card (1999, 2001) – supplemented by recent studies such as those of Oreopoulos (2006a, 2006b) – indicate, there is now strong evidence that schooling exerts a substantial causal impact on individual earnings. Similarly, recent research finds evidence of causal linkages between education and numerous non-pecuniary outcomes (Grossman, 2005, Oreopoulos and Salvanes, 2009).. These include reduced participation in crime (Lochner and Moretti, 2004), greater civic participation (Dee, 2004; Milligan, Moretti and Oreopoulos, 2004), improved health and increased longevity (Lleras-Muney, 2005; Oreopoulos, 2007) and greater life satisfaction (Oreopoulos, 2007). There is also growing evidence of inter-generational impacts, implying that some of the benefits are received by the children of those receiving additional schooling (e.g. Plug, 2004; Oreopoulos, Page and Stevens, 2006; Black, Devereux and Salvanes, 2008).

Although these and other consequences of additional schooling are increasingly becoming understood, much less is known about the mechanisms through which schooling exerts such powerful effects. Does schooling enhance individuals' cognitive skills such as literacy, numeracy and problem-solving skills, thus enabling them to perform more complex tasks in the workplace, increasing their value to employers? As Sen (1999) emphasizes, individuals without basic literacy and numeracy skills cannot assume a full and equal role in social and political discourse. If schooling plays an important role in the production of basic literacy and numeracy skills, low earnings and low levels of civic participation could be a consequence of limited education. Or do the consequences of education arise because additional schooling enhances non-cognitive skills such as the ability to meet deadlines, time management skills, and "people skills" – the ability to get along with others and to work effectively in teams? Another possibility is that additional education – to the extent that it is associated with higher earnings -- relaxes budget constraints. Improvements in health and well-being could be associated with higher income, to the extent to which income is not taken into account in studies of the relationship between schooling and various non-pecuniary outcomes. Finally, education may alter individual preferences – making people more "forward looking" and thus more willing to make investments – such as adopting healthy behaviors – that pay off in the future.

The purpose of this paper is to investigate the extent to which the impacts of education arise from the effects of schooling on cognitive skills and the consequences of these skills for pecuniary and non-pecuniary individual outcomes. Specifically, we provide estimates of the fraction of the return to schooling estimated in previous studies can be attributed to the combined effect of education on the production of cognitive skills and the value placed by cognitive skills in the labour market. We also examine the extent to which the impacts of schooling on health arise because of their impacts on literacy and numeracy skills.

Examining the importance of cognitive skills production seems a natural starting point for beginning to understand why schooling has powerful effects on many dimensions of individuals' lives. The concept of human capital has traditionally emphasized the acquisition of such skills as part of the decision of how much schooling the individual should invest in. Although education has multi-dimensional objectives, school systems around the world are judged, at least in part, by their ability to impart basic literacy, numeracy and analytical skills to students. Further, the importance of literacy, numeracy and problem-solving skills is often emphasized by employers.

Key to our investigation is a rich source of data on the literacy, numeracy and problem-solving skills of a representative sample of the adult Canadian population. These data also contain information on individual outcomes such as earnings, civic participation and health, as well as educational attainment. Using these data we study the causal impact of education on cognitive skills, concluding that schooling exerts a strong effect on these skills. Interestingly we find that there is little effect of age on cognitive skills. We then estimate the impact of schooling on individual outcomes using methods similar to those use din previous studies. Introducing measures of cognitive skills into these equations allows us to assess the extent to which estimated returns to schooling reflect the cognitive skill production mechanism.

The paper is organized as follows. The next section outlines a simple conceptual framework that underlies our analysis. Section 3 describes our data and its suitability for studying the cognitive skill production mechanism, while section 4 presents estimates of the causal impact of formal schooling on literacy, numeracy and problem-solving skills. The fifth section examines the extent to which typical estimates of the returns to schooling reflect the combination of the effect of schooling on cognitive skills and the way these skills are rewarded in the labour market. Section 6 carries out a similar analysis of estimated impacts of education on health. Section 7 concludes.

2. Conceptual Framework

This section sets out a simple framework for considering earnings generation and its relationship to cognitive skills. We distinguish skills (personal characteristics that aid in productivity in specific tasks and which can be acquired by the individual) and abilities (innate, productive characteristics). In this taxonomy, skills include cognitive skills such as literacy and non-cognitive skills such as persistence and conscientiousness. The key distinction is that between attributes that are acquirable (skills) and those that are innate (abilities).

Assume that each worker potentially possesses a range of skills and can possess each of them in varying amounts. To simplify the exposition we will couch our discussion in terms of three skills. Individual earnings are determined according to some function of the skills an individual possesses and puts into use, as follows:

$$1)\quad E_i = f\ (G_i^1,\ G_i^2,\ G_i^3) + \varepsilon_i$$

where, E_i are earnings for individual i in our sample year, G_i^k is the amount of skill k that person i sells in the market, and ε_i is a disturbance term that is independent of the skills. We think of the disturbance term as capturing either individual idiosyncratic events that are independent of the skill levels or measurement error in earnings. We interpret the f(.) function as an earnings generation function derived ultimately from an overall production function that is separable in other (non-skill) inputs. Thus, by characterizing the f(.) function, we can learn about the importance of the various skills and how they interact in production. To help in focussing ideas, we will think of G^1 as cognitive skills of the type measured in literacy tests, G^2 as other (perhaps manual) skills that are not captured in such tests and might be acquired through work experience, and G^3 as non-cognitive characteristics such as persistence that might be partly acquired through schooling.

$$2)\ r_k = \frac{\partial f}{\partial G^k}\ (G_i^1,\ G_i^2,\ G_i^3), \quad k = 1,\ldots,3$$

Based on 1), we can construct a set of skill price functions given by,
Note that the prices can vary according to the complete bundle of attributes the individual sells. We are interested in characterizing this set of skill price functions. Once we have done that, we will know the relative importance of the various skills in production and also whether the different skills are complements or substitutes in production.

Characterizing either 1) or 2) would be a relatively straightforward exercise if we observed the skills, G_i^k. Typically, of course, we do not observe them. What we do observe is some of the inputs used in generating the skills. To see how they enter our framework, consider a set of production functions for generating the skills:

$$3)\ G_i^k = h_k\ (\ yrs_i,\ \exp_i,\ \theta_i)$$

where *k* indexes the attribute type, yrs corresponds to years of formal schooling, exp is years of experience in the work force and θ is a vector of innate abilities. Note that we differentiate between abilities (which are innate) and skills (which may be acquired and are directly useful in production). The vector of abilities, θ, may include both cognitive and non-cognitive elements. That is, non-cognitive abilities such as persistence could be useful in generating both non-cognitive and cognitive skills.

If we do not observe the G_i^{k}'s directly, we can obtain an estimating equation by substituting the equations given by 3) into 1). This then yields a quasi-reduced form specification for annual earnings given by,

$$4)\ E_i = g(\ yrs_i,\ \exp_i,\ \theta_i) + \varepsilon_i$$

Thus, we are considering an hierarchical model in which covariates commonly used in wage regressions are inputs into skill production and these skills (plus an independent error term) determine wages.

Now, let us examine the partial derivatives of earnings with respect to each of the skill production inputs (e.g., schooling, experience or an element of the ability vector). The partial derivative associated with one of the inputs, x, can be expressed as,

$$5)\ \frac{\partial E}{\partial x} = \frac{\partial f}{\partial G^1} * \frac{\partial h_1}{\partial x} + \frac{\partial f}{\partial G^2} * \frac{\partial h_2}{\partial x} + \frac{\partial f}{\partial G^3} * \frac{\partial h_3}{\partial x}$$

where, we suppress the i subscript for simplicity. Thus, if x corresponds to years of schooling, yrs, then equation 5) says that the observed effect of an additional year of schooling reflects the effects of an extra year of education on the production of each attribute times the price paid for that attribute. It is apparent from equation 5) that with measures only of earnings and observable inputs used in producing attributes, we cannot make any statements about skill production or how skills combine in production apart from statements that either a critical combination of the derivatives on the right hand side of 5) are zero (and, hence, $\delta E/\delta x = 0$) or some of them are not. If we have individual observations on a skill, e.g., G^1, however, we can potentially say much more.

With G^1 observed, our quasi-reduced form earnings function becomes:

$$6)\ E_i = g^*(G_i^1,\ yrs_i,\ \exp_i,\ \theta_i) + \varepsilon_i$$

The derivative of this function with respect to G^1 corresponds to the attribute price function, r_1 - though, now we need to express the price as a function of yrs_i, exp_i, and θ_i :

$$7)\ r_1 = \chi(G_i^1,\ yrs_i,\ \exp_i,\ a_i)$$

With the price function given in 7), we cannot fully specify the interactions of G^1, G^2 and G^3 in production but we can learn more about them. In particular, the derivatives of r_1 with respect to the skill production input, x, is equal to (again suppressing the i subscript):

$$8)\ \frac{\partial r_1}{\partial x} = \frac{\partial r_1}{\partial G^2} * \frac{\partial h_2}{\partial x} + \frac{\partial r_1}{\partial G^3} * \frac{\partial h_3}{\partial x}$$

Further, we can consider the derivative of g* in equation 6) with respect to x:

$$9)\ \frac{\partial g^*}{\partial x} = \frac{\partial f}{\partial G^2} * \frac{\partial h_2}{\partial x} + \frac{\partial f}{\partial G^3} * \frac{\partial h_3}{\partial x}$$

With observed values for the derivatives, $\delta r_1/\delta x$ and $\delta g^*/\delta x$, we may be able to place restrictions on the f function. Thus, the fact that $\delta h_2/\delta x$ and $\delta h_3/\delta x$ appear in all these functions raises the possibility of putting restrictions on the production functions for the non-observed skills based on sign and significance patterns in the observed derivatives. With these restrictions in hand, we may further be able to place restrictions on the $\delta r_1/\delta G^k$ terms. In our framework, these latter terms reflect interactions in production of the non-observed skills with G^1.

We can also learn something about the production of G^1 from the differences between the derivatives, 5) and 9). These derivatives (e.g., the derivative of earnings with respect to schooling first not conditioning and then conditioning on G^1) differ by the term $\delta f/\delta G^1 * \delta h_1/\delta x$. Thus, the difference between these observed derivatives reflect the extent to which the coefficient on, for example, schooling in a standard earnings regression reflects the channel of added schooling generating added earnings through added cognitive skill creation. Given that we observe G^1 directly, we can go further and derive insights into the production of G^1 (as reflected in the $\delta h_1/\delta x$ terms) through direct estimation. That is essentially what we did in the previous section, where our main conclusions were that literacy is primarily produced through formal schooling and deteriorates with time after the person leaves school. The latter effect may be offset to some (likely relatively minor) extent by having a job that uses literacy skills.

Note that, as expressed in equation 7), the skill price facing an individual will be a function of the ability vector, θ_i. In terms of our framework, this implies that the impacts of elements of the θ_i vector on r_1 can be written as in equation 8) with x replaced by the relevant element of θ_i. That is, if we could observe θ_i, we could learn more about the interactions of the various skills in production. In terms of empirical implementation, the fact that $r_1 = \delta E/\delta G^1$ could vary with unobservables points to the use of quantile regressions since they effectively allow us to observe derivatives of earnings with respect to observable variables at the different values of the unobservables that generate the various conditional quantiles. Moreover, if θ_i were a scalar rather than a vector, the h() functions were monotonic in θ_i and the f function were monotonically increasing in skills then increasing quantiles of the earnings distribution, conditional on G^1, yrs and exp, would be associated with increasing values of θ_i and we could sign $\delta r_1/\delta\theta$ based on how $\delta E/\delta G^1$ varies across increasing conditional earnings quantiles.

3. Data

The main dataset we use in this investigation is the International Adult Literacy and Skills Survey (IALSS), the Canadian component of the Adult Literacy and Life Skills Survey (ALL). Statistics Canada carried out this survey in 2003 to study the skills of Canadians. The IALSS includes standard questions on demographics, labour force status and earnings, but it also measures literacy and related cognitive skills in four broad areas: Prose Literacy, Document Literacy, Numeracy, and Problem Solving. Perhaps of most importance for our purposes, the IALSS did not attempt to just measure abilities in math and reading but tried to assess capabilities in applying skills to situations found in everyday life. Thus, the Prose questions in the surveys assess skills ranging from items such as identifying recommended dosages of aspirin from the 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.” The Document questions, which are intended to assess capabilities to locate and use information in various forms, range from identifying percentages in categories in a pictorial graph to assessing an average price by combining several pieces of information. The Numeracy component ranges from simple addition of pieces of information on an order form to calculating the percentage of calories coming from fat in a Big Mac based on a nutritional table. Thus, the questions are related to implementation and use of skills in the real world and are intended not just to elicit current capacities but also adaptability to answering questions in other contexts (Murray, Clermont and Binkley, 2005).[1] This is an important point for the interpretation of our results since we want to interpret the test results as revealing job relevant skills at the time of the interview rather than inherent abilities.

In addition to providing measures of cognitive skills used in daily life, these data have two important features. First, like the previous International Adult Literacy Survey (IALS), they provide measures of skills for a representative sample of the adult population. Other measures of abilities or skills typically take the form of student achievement while in school. Second, the sample size is large, allowing analysis that would simply not be feasible with a much smaller sample. Our sample contains observations on 23,038 individuals, in contrast to the 1994 Canadian IALS that had 5660 observations.[2]

The survey covers individuals age 16 and over, and this is also the age range we focus on in our analysis. In order to focus attention on the Canadian educational system and cognitive skill generation in Canada, we exclude from our sample anyone born outside of Canada.We also drop individuals who list their main activity as "student" in order to focus on the effect of completed schooling and what happens subsequently to individual skills. We also drop the over-sampled aboriginal population, reserving a careful analysis of these individuals for a separate paper. The result is a sample of size 13,901, which forms the basis of our initial analysis of the determinants of cognitive skills. However, when we turn to our investigation of the impact of cognitive skills on earnings, we restrict ourselves to those employed at the time of the survey. We also drop the self-employed and workers with weekly earnings that are less than $50 and over $20,000. The latter restriction cuts out a small number of individuals with earnings that

[1] The IALSS builds on the IALS survey that was carried out in several countries during the period 1994 to 1998. Two of the skill domains – prose literacy and document literacy – are defined and measured in the same manner in IALS and IALSS.

[2] Sample sizes for the IALS surveys carried out in the mid- to late-1990s were typically less than 6,000, even for large countries such as the U.S. and Germany. The large Canadian sample size is also unique in the current round of data collection that started in 2003.

are substantial outliers relative to the rest of the sample. We exclude the self employed because we wish to assess the way skills are rewarded in the labour market, and self employed earnings reflect both that remuneration and returns to capital. We include both males and females throughout, dividing the analysis on gender lines in some places. Finally, we use the sample weights throughout the analysis, so all summary statistics and regression estimates are nationally representative.

For the earnings analysis our dependent variable is weekly earnings. In the IALSS respondents are first asked about their standard pay period and then asked about typical earnings in that pay period. Using these responses we construct a weekly earnings measure for each paid worker. Thus, for example, in the case of individuals who report that they are paid monthly we divide their usual monthly earnings by 4.333.

A salient feature of the data is the strong correlation among the various cognitive skill measures. The correlation between the Prose literacy and Document literacy scores is 0.96, that between Prose literacy and Numeracy is 0.90, and the correlation between Prose literacy and Problem Solving is 0.93. Further, a principal components analysis indicated only two principal components with the first being vastly more important and placing equal weight on all four scores. Thus a simple average of the four scores captures much of the information available in the skill measures. This is the skill measure that we use in the analysis.

4. The Generation of Cognitive Skills

This section examines the sources of literacy, numeracy and problem-solving skills (which we refer to simply as "cognitive skills" or "literacy skills"). We focus on the average skill score as our representative measure. Our regressions use the log of the average score as the dependent variable so our estimated coefficients can be interpreted as showing impacts in terms of percentage changes in skills.

Before presenting the estimation results, we set out a brief, heuristic model of cognitive skill generation. The model will help to put our estimates in context as well as providing guidance in thinking about identification issues. Consider a simple model in which individuals start out at birth endowed with two key characteristics: their ability and parental resources. By parental resources, we mean something quite broad, incorporating both parental income and parental willingness and ability to support their children's education and literacy acquisition. Pre-school children begin to acquire literacy based on these fundamental characteristics (ability and parental resources). Once they enter school, these characteristics interact with characteristics of the school such as teacher quality, class size and the attitudes and abilities of peers. New additions to cognitive skills with each year of schooling are then functions of ability, parental resources, school characteristics and the literacy and numeracy level at the beginning of the period. These influences may interact in complicated ways. These additions continue until the legal school leaving age. After that point until the end of high school, students make a decision each year on whether to continue in school. That decision will be a function of ability, parental resources and school characteristics, again, but it is also likely to be a function of literacy acquired to that point. The more literate and numerate a student is, the less onerous they are likely to find school and, thus, the more likely they are to choose to stay an extra year. Finally, after high school, whether an individual continues to go to school will be determined by a combination of their own decision to apply to continue and the decision of the college or university on whether to admit them. The latter decision will likely be a function of the student's cognitive skills as reflected in her grades. Thus, schooling and cognitive skills are co-determined with extra years of schooling leading to increased literacy and numeracy but increased skills also leading to more years of schooling, especially after the legal school leaving age. Indeed, once we account for expectations, the inter-relation between the two may be even tighter. Individuals who do not expect to continue with school past the legal minimum may rationally under-invest in acquiring literacy and numeracy skills while they are in school.

Once individuals leave school, skill acquisition is likely more difficult. Literacy and numeracy skills may be acquired on the job if they are needed for carrying out tasks at work but otherwise further acquisition would require active investment in non-work hours. Indeed, it seems quite possible that individuals could lose cognitive skills after they leave formal schooling if those skills depreciate when they are not used.

We are interested in characterizing as many of the components of literacy, numeracy and problem-solving generation as possible. In particular, we are interested in the relationship of literacy and numeracy to parental resources since that relationship is fundamentally linked to notions of equity: to the extent that one generation's literacy hinges on the resources of the previous generation, differences in literacy can be seen as arising from characteristics beyond the control of the people involved. We are also interested in the relationship between formal schooling and cognitive skills since this is a main channel through which we could hope to affect the skill distribution. Finally, we are interested in whether literacy and numeracy decline or rise after leaving school and how this process is related to characteristics of individuals – whether cognitive skills have a "use it or lose it" character. Many of these relationships reflect causal relationships that are difficult to establish definitively. We will make efforts to estimate the causal parameters where the data permit but some of what we discuss is necessarily in the form of correlations rather than clear causal impacts.

Figure 1 shows the partial relationship between cognitive skills and years of schooling, after controlling for age, gender, parental characteristics, province of residence and urban/rural residence. The relationship is upward sloping, close to linear, but with a small amount of concavity especially after 16 years of schooling. The latter is perhaps not surprising because the IALSS does not attempt to measure higher-level skills such as those that would be acquired in graduate school. In the regression results that follow we restrict the sample to those with 16 years of schooling or less. Within this range the partial relationship between average skills and years of schooling is approximately linear, which simplifies our empirical analysis.[3] This is also the range within which compulsory schooling laws, one of our instrumental variables for education, are most likely to be binding.

The first column of Table 2 presents our simplest OLS regression in which the dependent variable is the log of the average skill score and the independent variables are age, age squared, years of schooling, gender, dummies for residence in small and large urban areas, and province of residence.[4] All the variables are statistically significant but this does not mean their actual impacts are sizeable. Thus, the estimates show that women have lower average skills than men (conditional on school and age) but only by 1.1%. Similarly, the age and age squared coefficients are highly statistically significant but

[3] An OLS regression of log average skill on years of schooling, years of schooling squared and other covariates listed in Table 2 yields an insignificant coefficient on the quadratic years of schooling term.
[4] Estimated coefficients on the urban – rural and province of residence dummies are not shown in the table.

together they imply that the impact of an extra year of age on literacy and numeracy skills is actually -0.1% at age 30. This finding that there is essentially no relationship between literacy and either age (or experience) is a key part of the discussion in Green and Riddell (2003). The one relationship that is economically substantial is the one between cognitive skills and schooling. One extra year of schooling increases literacy and numeracy by 3.4%. This is very similar to what Green and Riddell (2003) calculated using the 1994 IALS survey.

The second column of Table 2 adds variables on parental education and immigrant status. Introducing these variables has virtually no impact on either the gender or schooling variable effects. However, including them leads to a large (in percentage terms) increase in the age coefficient. Given that the coefficient on the age squared variable also becomes more negative, the net effect of age is still quite small. The parental education variables are jointly highly significantly different from zero but, perhaps surprisingly, the effect is found almost entirely at low levels of parental education. Having a parent (either mother or father) who is a high school drop out decreases average cognitive skills by between 2% and 3%. However, parental education beyond high school has no further impact on skills. Interestingly, not knowing a parent's education level (which is the case for approximately 8% of the sample) has a strong effect, being associated with approximately 5% to 6% lower literacy. While we included this variable in order to allow us keep the observations for which parental education is missing, it seems possible it is actually capturing something real. For example, children who do not know a parent's education likely did not have a close relationship with that parent. Thus, the estimated coefficient may reflect the extent to which literacy and numeracy are generated through direct parental involvement. Finally, having a parent who is an immigrant has no impact. We also tested specifications in which we included a set of parental occupation dummy variables but these were never jointly statistically significant. In particular, a test of the hypothesis that the set of father's occupation dummy variables jointly had zero effects has an associated P-value of .13. The same test for mother's occupation has a P-value of .79. We also find that a dummy variable representing whether the individual's mother was working when the individual was 16 does not have a statistically significant effect. Overall, the results point to a surprisingly weak association between cognitive skills and parental background. Only schooling seems to have a substantial impact on literacy generation.

As we discussed earlier, cognitive skills and years of schooling are likely to be jointly determined. In that case, the coefficient on schooling provides a biased estimate of the impact of schooling on literacy. We attempt to address this in two ways. First, biases may arise because of a correlation between literacy and schooling arising from unobserved ability. If high ability people do not view it as particularly costly to either acquire literacy or go to school then we could observe a strong positive coefficient on schooling in our regression because years of schooling is proxying for ability rather than as a reflection of a causal impact of schooling on skills. This problem can be addressed if we have a measure of ability since once we control for ability, any relationship between schooling and literacy cannot be due to an omitted ability term. Note, though, that many studies that try to control for ability (in, for example, earnings regressions) actually use scores on tests similar to our cognitive skills tests. What we would require is a test score from a very young age - before the process we are trying to study really begins. Since we don't have that, we instead try to proxy for ability using two variables that are plausibly related to it. In particular, in the third regression, we include a dummy variable equalling one if the person agreed or strongly agreed with the statement that they got good grades in math when they were in school and another dummy variable equalling one if the respondent agreed or strongly agreed with the statement that teachers often went too fast and the person often got lost. Either of these could plausibly be seen as proxies for innate ability. Both of these variables enter significantly, with people who claimed to have gotten good grades in math having 4.0% higher scores and those who thought teachers went too fast having 2.0% lower skill scores. However, including these variables has little impact on the other estimated coefficients, including the impact of schooling on cognitive skills.

An alternative approach to the problem of identifying a causal effect is to use an instrumental variable strategy. We use two instrumental variables for schooling. First, we use changes in compulsory schooling laws over time and across provinces. Changes in these laws have been shown to have significant effects on educational attainment, and have been a commonly-used instrument for education (see, for example, Acemoglu &

Angrist, 2000; Lochner & Moretti, 2004; Milligan, Moretti & Oreopoulos, 2004; and Oreopoulos, 2003, 2006a).

Using the compulsory schooling laws data compiled by Oreopoulos (2003, 2006a), we first create five indicator variables to indicate whether the youngest school leaving age is 12, 13, 14, 15, or 16, and then another three indicator variables to indicate whether the oldest school entry age is 6, 7, or 8. The linkage between the IALSS data and data on compulsory schooling laws is established based on the birthplace of each individual and the year when the individual turned 14 for matching school leaving age or 6 for matching school entry age. Schmidt (1996) finds that the effects of compulsory schooling laws in the U.S. were largest when matched to individuals at age 14. Acemoglu and Angrist (2000), Lleras-Muney (2002), Schmidt (1996), and Goldin and Katz (2003) adopt the same procedure in their studies based on the U.S. data, while Oreopoulos (2003, 2006a) adopts the same procedure when analyzing Canadian data.

We also construct a variable for the difference between the youngest school leaving age and the oldest school entry age, which corresponds to the number of years spent in school for an individual who waited to enter school until reaching the required school entry age and who left school immediately after reaching the school leaving age. Acemoglu and Angrist (2000), Lleras-Muney (2002), and Oreopoulos (2003, 2006a) use a similar instrumental variable based on the number of mandatory school years in their research.

The second set of instrumental variables is the province where the individual resided when he or she was last in high school or middle school fully interacted with age. The idea behind this instrument, which was also used by Card and Krueger (1992) in their analysis of school quality in the U.S., is that different levels of public resources applied to schooling in different provinces for different generations will lead to different schooling outcomes for otherwise identical individuals. This instrument will be valid if provincial education resources and policies while in high school influence schooling outcomes but do not directly influence the production of cognitive skills. In implementing this approach it is important to control for current province of residence in both the first stage (schooling regression) and the second stage (cognitive skills regression). Province of current residence may be related to skills if more literate individuals choose to migrate to provinces with a higher proportion of high skill jobs and low literacy individuals chose to move to, for example, provinces with large numbers of resource jobs. In that case, to the extent that province of residence during high school and current province of residence are correlated, the province of residence would pick up this migration effect rather than the schooling effect we want it to capture. Controlling for province of current residence addresses this problem and means that we are identifying the schooling effect from people who currently reside in the same province but were schooled in different provinces at different times.

The results from our two stage least squares estimation using these instrumental variables are reported in columns 3 to 6 of Table 2. The first stage regressions, in which years of schooling is the dependent variable, are reported in Table 3. These indicate that, as expected, parental education is strongly positively related to years of schooling. There are also some interesting gender differences. For example, having a father with a university bachelor's degree has a large and statistically significant coefficient while having a mother with a university degree does not. Having parents who are immigrants is also positively associated with years of schooling. Those who live in large urban areas also have more schooling.

Importantly, both sets of instruments are jointly highly statistically significant, indicating that the requirement that the instrument exerts a significant influence on the endogenous variable is satisfied. The first stage F statistics corresponding to the hypothesis that the instrumental variables are jointly equal to zero are shown in the bottom row of the table – all are in the range 20 to 30. The estimated coefficients associated with the school leaving age variables indicate that raising the school leaving age to 15 is associated with an increase in years of schooling of 0.9 years, while an increase in the minimum dropout age to 16 increases educational attainment by 0.6 years.

The IV estimates in columns 4 to 6 provide remarkably similar estimates of each of the coefficients. For example, the IV estimate of the schooling effect ranges from 4.3% to 4.5%. This estimate is about 40% higher than the corresponding estimate in column 2, implying even stronger schooling effects than those estimated with OLS. Interestingly, once we instrument for schooling, the parental background variables become smaller in magnitude, although most retain statistical significance. As in earlier specifications, gender and age continue to have small impacts on literacy. We do not present the coefficients corresponding to the provincial dummy variables for the sake of brevity but they show that the Atlantic provinces and Ontario have essentially similar cognitive skill levels, Quebec has significantly lower skill levels and the Prairies and BC all have significantly higher levels. Our main conclusion is that, if the assumptions underlying our instruments are correct, these results indicate that education has a strong causal effect on cognitive skills and that schooling is the dominant determinant of literacy, numeracy and problem-solving skills. To put the estimated effect in perspective, completing four extra years of schooling (e.g., moving from being a high school graduate to a university graduate) implies an 18% increase in literacy, based on the IV estimates. This would be enough to move the individual from the median to above the 75^{th} percentile of the cognitive skill distribution in 2003.

5. Cognitive Skills and the Returns to Schooling

We present estimation results from mean regressions using the log of weekly wages in Table 4. The first column shows the results from a standard regression with a female dummy, years of schooling, experience and experience squared as covariates. As before, controls for province of residence and urban/rural status are included but not reported. The results are extremely standard in terms of their magnitudes and sign patterns (see Card (1999) for a review of the very large relevant literature). In the second column, we add the average cognitive skill variable. We have also estimated specifications in which we include all 4 scores separately. In those estimations, document literacy enters statistically significantly with a coefficient of .0021, numeracy enters statistically significantly with a coefficient of .0011 and problem solving and prose literacy have smaller, not statistically significant and offsetting coefficients. Note that these significant separate effects essentially add up to the estimated coefficient on average skill measure presented in Table 4. This suggests that numeracy may have separate effects from the other three types of literacy and that its effects are smaller than whatever is being captured (primarily) in the document score.

Adding the average skill score leads to a reduction in the derivative of log earnings with respect to education from .087 without the skills variable to .069 when it is included. This is a reduction of about 20%, suggesting both that literacy and numeracy skills play an important role in the returns to education and that education has a substantial impact on earnings over and above the impact related to production of literacy skills. In contrast to the effect on the schooling coefficient, the coefficients on the experience variables are unchanged when we introduce the cognitive skills variable. This is a direct reflection of the fact that literacy and numeracy generation is not related to age or experience in the cross-section. In terms of the framework set out above, experience does not enter the skill production function and so the first term on the right hand side of equation 5 is zero. The implication is then that the derivative with respect to experience is the same whether or not we condition on cognitive skills. Finally, the direct impact of cognitive skills on earnings is substantial. A 25 point increase in the average skill score (the equivalent of about 1/2 of a standard deviation in the skill score distribution) has an impact equivalent to an extra year of schooling.

As mentioned in our theoretical discussion, our estimation may be affected by omitted variables bias. In particular, the error term in the regression may include various types of ability which are correlated with the included variables. Typically, ability is assumed to affect both schooling choices and earnings, leading to biased estimates. Given our specified model, if we assume that unobserved cognitive abilities only affect the generation of cognitive skills and other, non-cognitive abilities do not affect the generation of cognitive skills then literacy will not be correlated with the error term and does not, itself, represent an endogeneity problem. However, we still need to address the potential endogeneity of schooling. We do this using province in which the individual resided and interactions of it with age as our instrument as we did in the cognitive skills estimation. As before, we control for province of current of residence at the same time.

The results from instrumenting for schooling when the cognitive skills variable is not included are reported in the third column of Table 4. Instrumenting reduces the coefficient on schooling slightly, which is suggestive of endogeneity problems with the simple OLS estimation. In the fourth column, we repeat this exercise but also include the average skill measure. The instrumenting yields a somewhat smaller schooling coefficient than in the simple OLS results in column 2. As in the simple OLS estimates, introducing the average literacy score reduces the schooling coefficient by approximately

20%. The skill score coefficient itself is identical to the OLS coefficient in column 2. Thus, our main conclusions our not altered by instrumenting.

As discussed earlier, our theoretical framework points to advantages from using a quantile regression framework. We present the results of quantile regression estimation for the 10th, 25th, 50th, 75th and 90th quantiles in Table 5. The key implications from the estimation are as follows. First, returns to both schooling and experience decline across quantiles. The finding of heterogeneity in returns to education across the earnings distribution has been observed by previous authors. 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 10th to the 50th 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.

Perhaps the most interesting result in Table 5 is the relative lack of variation in the coefficient on the cognitive skills measure across the quantiles. While the coefficient for the 10th quantile appears substantively smaller than those at the other quantiles it is not actually statistically significantly so. Moreover, if we run quantile regressions at the quantiles directly surrounding the 10th quantile (e.g., the 5th and 15th quantiles), we obtain estimated literacy effects that are almost exactly the same as those reported for the upper quantiles - the 10th quantile appears to be a bit of a statistical outlier. In the context of our theoretical model this implies that cognitive skills do not interact with other attributes in earnings generation. Thus, other attributes or skills such as persistence and leadership skills (Kuhn and Weinberger (2005)) may contribute to individual earnings but their contributions are not enhanced by having more literacy skills. Cognitive skills are not a silver bullet that both contributes directly to earnings and increases returns to other attributes.

In summary, our results suggest that literacy, numeracy and problem-solving skills are important determinants of earnings but that there is a great deal of earnings variation that is accounted for by other factors. About 20% of the return to schooling estimated in previous studies can be attributed to the combined effect of formal education on these skills and the value placed on cognitive skills in the labour market.

6. Conclusions

A substantial body of recent research provides evidence that formal education exerts a powerful influence on individuals' lifetime earnings. This research concludes that this influence is causal in nature, rather than simply reflecting a positive correlation between schooling and earnings. In addition there is growing evidence of causal impacts of education on various non-pecuniary individual outcomes, such as civic participation, health and longevity, participation in crime, and life satisfaction. However, little is known about the mechanisms that underlie these causal impacts. The purpose of this paper is to investigate the extent to which the estimated impacts of formal schooling on outcomes reflects the impact of education on the production of cognitive skills and the influence of cognitive skills on individual outcomes such as earnings and health. To do so we use a rich data set containing measures of literacy, numeracy and problem-solving skills for a representative sample of the adult population.

Our investigation yields several noteworthy findings. First, we provide strong evidence that education has a substantial causal effect on cognitive skills, and that formal schooling is the dominant determinant of basic literacy, numeracy and problem-solving skills. Our instrumental variables estimates indicate that each additional year of schooling raises average skills by about 4.5% or about one-quarter of a standard deviation of the skill score distribution. To put this in perspective, completing four additional years of schooling (e.g. moving from being a high school graduate to a university graduate) would move the individual from the median to above the 75th percentile in the skill distribution. In addition, age (or work experience) has little impact on cognitive skills, suggesting that the positive relationship between experience and earnings arises for other reasons. Furthermore, parental characteristics have only modest effects on literacy and numeracy skills. Having a mother or father with less than high school education has a modest negative effect on cognitive skills, but having a parent with education beyond secondary school has no effect. Similarly, having immigrant parents has no effect. The influence of parental characteristics on skills arises indirectly through their powerful influence on the child's education rather than directly.

When we estimate log earnings equations similar to those that have appeared in previous papers we obtain results similar to those in the literature on schooling and earnings: returns to schooling in the order of 7% to 9%. However, when we also control for cognitive skills these coefficient estimates drop by about 20% (OLS) and 30% (IV). The difference between these two sets of estimates represents the combined effect of education on the production of cognitive skills and the value placed on these skills in the labour market. Thus according to our preferred IV estimates, about 30% of the return to schooling represents the role of formal education in the production of literacy, numeracy and problem-solving skills. This is a substantial component of the return to education, but the fact that the coefficient on schooling remains large and statistically significant after controlling for skills suggests that schooling affects earnings via other mechanisms such as its influence on non-cognitive skills such as reliability, "people skills" and persistence.

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Figure 1

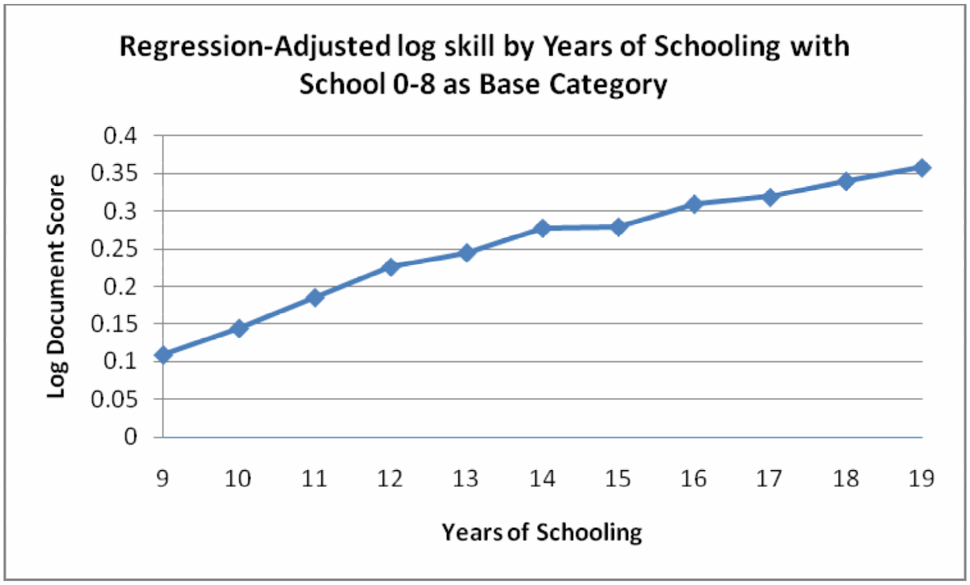


Figure 2

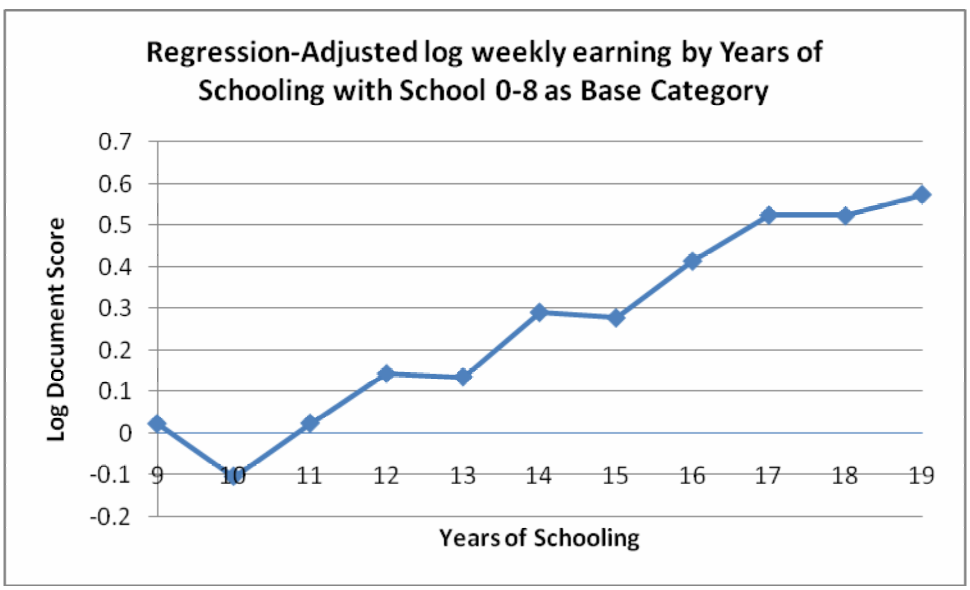
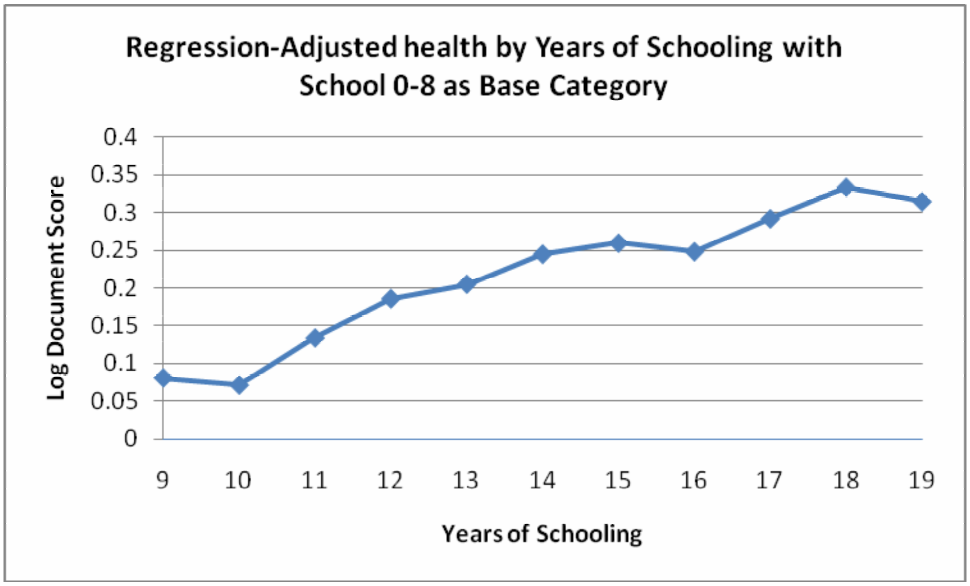


Figure 3



Regression-Adjusted health by Years of Schooling with School 0-8 as Base Category
Log Document Score
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
9
10
11
12
13
14
15
16
17
18
19
Years of Schooling

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Individual Characteristics				
Female	.508	.500	0	1
Age	44.746	16.834	17	94
High school graduate	.708	.455	0	1
Years of schooling	11.993	2.643	0	16
Parental characteristics				
Mother's education				
Less than high school	.473	.499	0	1
High school	.260	.439	0	1
Some post secondary	.122	.327	0	1
BA or more	.062	.242	0	1
None reported	.082	.275	0	1
Father's education				
Less than high school	.515	.500	0	1
High school	.194	.396	0	1
Some post secondary	.112	.315	0	1
BA or more	.086	.281	0	1
None reported	.093	.290	0	1
Immigrant parents				
Immigrant mother	.152	.359	0	1
Immigrant father	.175	.380	0	1
Cognitive skills				
Prose score	275.623	48.393	83.8	435.8
Document score	272.852	50.846	82.8	430.2
Numeracy score	263.345	51.506	72.8	429.6
Problem solving score	268.548	46.655	35	408.2
Average skill score	270.092	47.419	96.95	416.05
Civic Participation, Health and Well-Being				
Voted in federal or provincial election	.787	.410	0	1
Participate political organization	.035	.183	0	1
Participate community/school	.186	.389	0	1
Healthy	.566	.496	0	1
Satisfied with life	.828	.378	0	1
Compulsory schooling laws				
Mandatory school years	9.007	1.076	5	11
School entry age 5	.009	.094	0	1
School entry age 6	.608	.488	0	1
School entry age 7	.310	.462	0	1
School entry age 8	.073	.260	0	1
School leaving age 12	.004	.061	0	1

School leaving age 13	.0003	.016	0	1
School leaving age 14	.136	.343	0	1
School leaving age 15	.318	.466	0	1
School leaving age 16	.540	.498	0	1
School leaving age 18	.001	.032	0	1
Number of observations	11929			

Table 2: Log of Average Skill Score Regressions

Variable	OLS 1	OLS 2	OLS 3	IV1	IV2	IV3
Female	-0.011**	-0.010**	-0.006	-0.013**	-0.014***	-0.014***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Years of Schooling	0.034***	0.031***	0.029***	0.043***	0.045***	0.044***
	[0.001]	[0.001]	[0.001]	[0.010]	[0.003]	[0.003]
Age	0.004***	0.006***	0.007***	0.005***	0.004***	0.004***
	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
Age Squared	-0.008***	-0.010***	-0.010***	-0.007***	-0.007***	-0.007***
	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
Mother's Education						
Less than High School	-	-0.031***	-0.032***	-0.023***	-0.022***	-0.022***
	-	[0.006]	[0.006]	[0.009]	[0.007]	[0.007]
Some Post Secondary	-	0.003	0.002	-0.001	-0.002	-0.001
	-	[0.007]	[0.007]	[0.008]	[0.007]	[0.007]
BA or More	-	0.007	0.006	0.005	0.005	0.005
	-	[0.012]	[0.011]	[0.012]	[0.012]	[0.012]
None Reported	-	-0.055***	-0.058***	-0.042***	-0.040***	-0.040***
	-	[0.011]	[0.011]	[0.015]	[0.011]	[0.011]
Father's Education	-					
Less than High School	-	-0.024***	-0.023***	-0.015	-0.014*	-0.014*
	-	[0.007]	[0.007]	[0.011]	[0.008]	[0.008]
Some Post Secondary	-	0.003	0.005	0.001	0	0
	-	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
BA or More	-	0.016*	0.022**	0.011	0.01	0.01
	-	[0.009]	[0.009]	[0.010]	[0.010]	[0.010]
None Reported	-	-0.048***	-0.046***	-0.032*	-0.029**	-0.029***
	-	[0.011]	[0.011]	[0.017]	[0.011]	[0.011]
Immigrant Mother	-	-0.001	-0.002	-0.004	-0.005	-0.005
	-	[0.008]	[0.008]	[0.009]	[0.009]	[0.009]
Immigrant Father	-	0.008	0.009	0.006	0.006	0.006
	-	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
Good Math Grades	-		0.040***			
	-		[0.005]			
Teachers Too Fast	-		-0.020***			
	-		[0.005]			
Constant	5.142***	5.155***	5.147***	5.044***	5.025***	5.028***
	[0.021]	[0.022]	[0.022]	[0.092]	[0.037]	[0.036]

Observations	11929	11929	11929	11929	11929	11929
R-squared	0.47	0.49	0.5	0.47	0.46	0.46

Notes:

1. Dummies of province of residence are included in all regressions.
2. Individuals are matched to the minimum schooling leaving age by province of birth.
3. In the first stage regression, people with schooling leaving age 12, 13, and 14 when they were 14 years old are chosen as the reference group. People with schooling leaving age 16 and 18 are grouped together due to the small number of observations with schooling leaving age 18 (12 observations).

Table 3: First Stage Results for Years of Schooling

Variable	IV 1	IV 2	IV 3
Dropout Age 15	0.904*** [0.148]		0.322** [0.150]
Dropout Age 16 or 18	0.571*** [0.165]		0.066 [0.169]
Age	0.125*** [0.012]	0.096*** [0.015]	0.083*** [0.015]
Age Squared	-0.159*** [0.013]	-0.159*** [0.011]	-0.149*** [0.012]
Mother's Education			
Less than High School	-0.644*** [0.113]	-0.569*** [0.099]	-0.579*** [0.098]
Some Post Secondary	0.346*** [0.114]	0.256** [0.105]	0.261** [0.105]
BA or More	0.163 [0.169]	0.171 [0.164]	0.166 [0.164]
None Reported	-1.111*** [0.186]	-0.864*** [0.161]	-0.872*** [0.161]
Father's Education			
Less than High School	-0.778*** [0.111]	-0.669*** [0.102]	-0.669*** [0.102]
Some Post Secondary	0.212* [0.127]	0.266** [0.126]	0.269** [0.126]
BA or More	0.491*** [0.142]	0.527*** [0.139]	0.531*** [0.139]
None Reported	-1.431*** [0.168]	-1.241*** [0.153]	-1.246*** [0.152]
Immigrant Mother	0.261** [0.125]	0.224* [0.118]	0.215* [0.119]
Immigrant Father	0.086 [0.123]	0.087 [0.117]	0.081 [0.117]
Live in Urban Area	0.041 [0.104]	0.059 [0.099]	0.055 [0.099]
Live in large Urban Area	0.404*** [0.097]	0.379*** [0.092]	0.384*** [0.092]
Constant	8.999*** [0.340]	11.182*** [0.515]	11.280*** [0.531]
Observations	11929	11929	11929
R-squared	0.26	0.4	0.4
First stage F statistics	21.74	38.42	35.67

Standard errors in parentheses. *, **, *** statistically significant at 10%, 5%, 1% level. Specifications IV1, IV2, IV3 include a compete set of current province of residence dummy variables. Specifications IV2 and IV3 include a complete set of province during high school dummy variables, and a complete set of interactions of the latter with age.

Table 4 Earnings Regressions

	OLS 1	OLS 2	IV 1	IV 2
Female	-0.411***	-0.407***	-0.404***	-0.399***
	(0.024)	(0.024)	[0.025]	[0.024]
Years of School	0.087***	0.070***	0.070***	0.049***
	(0.004)	(0.005)	[0.013]	[0.017]
Experience	0.065***	0.066***	0.067***	0.068***
	(0.004)	(0.004)	[0.004]	[0.004]
Experience Squared	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	[0.000]	[0.000]
Average Literacy Score	-	0.003***	-	0.003***
	-	(0.0003)	-	[0.001]
Constant	184.82***	4.269***	5.049***	4.328***
	(0.083)	(0.110)	[0.152]	[0.102]
Observations	7768	7768	7768	7768
R-squared	0.39	0.4	0.38	0.39

Standard errors in parentheses. *, **, *** statistically significantly different from zero at the 10%, 5% and 1% level of significance. All regressions include controls for province of residence and urban/rural status

Table 5: Quantile Earnings Regressions

	10th Quantile	25th Quantile	Median	75th Quantile	90th Quantile
Female	-0.48***	-0.46***	-0.36***	-0.36***	-0.36***
	(0.048)	(0.032)	(0.020)	(0.021)	(0.032)
Years of Schooling	0.079***	0.065***	0.069***	0.067***	0.057***
	(0.011)	(0.0065)	(0.0041)	(0.0042)	(0.0069)
Experience	0.088***	0.084***	0.059***	0.050***	0.042***
	(0.0063)	(0.0041)	(0.0025)	(0.0024)	(0.0036)
Experience Squared	-0.0015***	-0.0015***	-0.001***	-0.0008***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Average Literacy Score	0.0022***	0.0032***	0.0029***	0.003***	0.0028***
	(0.0007)	(0.0004)	(0.0003)	(0.0003)	(0.0005)
Constant	3.33***	3.67***	4.26***	4.62***	5.12***
	(0.19)	(0.12)	(0.083)	(0.079)	(0.13)
Observations	7768	7768	7768	7768	7768

Standard errors in parentheses. *, **, *** statistically significantly different from zero at the 10%, 5% and 1% level of significance. All regressions include controls for province of residence and urban/rural status