Literacy Skills, Non-Cognitive Skills and Earnings:
An Economist's Perspective

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1) Introduction

The statement that we are currently experiencing a fundamental technological change has become virtually a mantra of policy analysts and policy makers in Canada. The precise nature of the change varies from description to description but all have in common the central claim that the newer technologies and forms of organization favour more skilled over less skilled workers. Moreover, there is general agreement that the types of skills that are required with this new technology are cognitive skills rather than, say, craft skills. It is often argued that workers within an economy who do not possess these cognitive skills will be left behind and that economies that do not have enough skilled workers of this type will not acquire the new technology fast enough and will also be left behind. Thus, understanding the importance and distribution of cognitive skills in the economy is useful both for understanding how the income distribution will develop within the economy and how the economy will fare relative to its competitors.

This paper is concerned with investigating just how important cognitive skills are in the Canadian economy and, to a lesser extent, how these skills are produced. My approach will be very heavily that of an economist. I will attempt to determine the importance of cognitive skills by examining how such skills are remunerated. Essentially, the core idea behind the analysis is that if these skills are important then firms should be willing to pay for them. The more important they are relative to other skills, the more of total observed variation in earnings ought to be explained by them. If, as a model of technical change might suggest, they are important to firms and the supply of these skills is not keeping up with the growing demand then the return to possessing the skills ought to be high and rising. This is not to gainsay approaches where workers or firms are directly surveyed about their opinions on the current and forecasted importance of cognitive skills. Rather, my goal is to complement such analyses with a purely economic approach: if cognitive skills are important, they should show up in the pay structure.

At first glance, this investigation may seem a bit like quantifying the obvious. There is such widespread agreement on the notion that we are undergoing a major technological change, and on the nature of that change, that it seems clear that the answer to whether cognitive skills are important in the modern Canadian economy is yes. However, a long-standing line of research in economics might suggest otherwise. As part of attempts to establish the rate of return to schooling, many authors have included measures of "ability", by which is meant cognitive ability, in standard earnings regressions. Many of those studies, especially studies from the 1970s and 1980s, find very small coefficients on their measures of ability, suggesting that cognitive abilities are neither highly remunerated nor account for much of the total variation in earnings. I will argue that the ability measures typically used in those studies are not what we need to fully understand the importance of cognitive skills in the modern economy. In particular, I will argue that the cognitive abilities measured by IQ type tests should be seen as inputs in the creation of the cognitive skills we are ultimately interested in. These cognitive skills, in turn, are better measured by literacy tests of the type administered in the International Adult Literacy Survey. Hence, another way to state the goal of this paper is to investigate the importance of literacy skills in the Canadian economy. In any case, the distinction between abilities and skills is important in our context and part of the investigation will consist of setting out a framework for thinking about how their impacts on earnings might differ.

I am also interested in the question of how the literacy skills are generated and, to the extent it seems necessary, how we might engender a greater and more widespread acquisition of them. This will be a secondary theme in the paper. Given that we have measures of individual literacy skills, we can study the determinants of who possesses those skills and in what quantities directly. We will also see that we can learn quite a bit about how literacy skills are produced and how they interact with other skills by carefully studying patterns in earnings regressions.

Finally, asking how important are cognitive skills in determining earnings immediately raises the question, relative to what? It is not uncommon, especially among economists, to assume that cognitive skills are the only skills that are relevant in determining remuneration. Our only problem is that we do not fully measure those skills. However, the amount of the variation in earnings we can explain with our cognitive ability and skill measures is typically small. As a result, a growing group of economists is beginning to pay attention to the work of sociologists and psychologists on the importance of non-cognitive skills such as persistence, ability to communicate effectively, etc.. I will end the paper with a brief discussion of what economists are saying on the importance of these other skills. I apologize for not knowing the non-economics literature on this material to any great extent but, hopefully, that is part of what I will learn about at this conference.

The main conclusions from the analysis are as follows. First, literacy skills are very important determinants of earnings, with an increase in an individual's literacy score equivalent to 1/3 of the standard deviation of literacy scores in the population being associated with the same size increase in earnings as one extra year of schooling. Further, between 1/3 and ½ of the effect of schooling on earnings appears to arise because of the impact of schooling in generating greater literacy. Second, a review of the earlier literature indicates that literacy has been becoming more important as a determinant of earnings over the last three decades. Third, even though literacy skills are important, the fact that we can typically explain less than half the variation in earnings with measured covariates and the fact that the coefficient on schooling does not fall to zero once literacy measures are included points to the existence and importance of skills not captured in literacy tests - non-cognitive skills. Interestingly, our regression results indicate that these non-cognitive skills do not interact with cognitive skills in production. That is, having more of both types of skills increases earnings (i.e, both enhance productivity in our model) but having more non-cognitive skills does not enhance the productivity of the cognitive skills an individual has (or vice versa), in general. This is an intriguing finding that contradicts models that argue that non-cognitive skills are useful to the extent they enhance the ability of individuals to use their cognitive skills. It suggests that non-cognitive skills are productive in their own right.

I also look briefly at the generation of literacy skills. The main findings in this regard are that schooling and parental education are important in generating literacy skills but that labour market experience is not. Thus, increasing the literacy level of the Canadian workforce would require direct, active policies rather than just re-enforcing standard on-the-job training.

The paper proceeds in seven sections including the introduction. In the second section, I attempt to review what we know about the importance of cognitive skills from the existing economics literature. In fact, as I stated earlier, what we can learn from the existing literature is about the importance of cognitive abilities. Discussing that literature fully will require a brief overview of the problems involved in estimating the returns to education since most of these papers were written as part of an attempt to estimate those returns. In the third section, I will set out a framework for thinking about the contribution of various types of skills and abilities to earnings. This section can be skimmed or even skipped by the uninterested reader. The fourth section provides a brief description of the IALS, the main dataset available for estimating returns to literacy in Canada. The fifth section describes results from estimation using the IALS, working mainly off Green and Riddell(2001, 2001a). The sixth section provides an interpretation of the results from the IALS and a discussion of the growing literature on non-cognitive skills. The last

2) Sorting Out Earnings, Schooling and Ability

The question of how literacy skills are both generated and valued in an economy like

Canada's is deeply inter-twined with attempts to understand the impact of schooling on earnings. They are inter-twined both in terms of the intellectual considerations raised in studying each issue and in the history of how they have actually been studied. For that reason, we need to begin our discussion with a brief over-view of research into the returns to schooling.

The question of the causal impact of schooling on earnings outcomes is one of the oldest and most carefully studied issues in labour economics. It holds interest because of its relationship to two key economic issues: equity and growth. If increasing schooling leads to increases in earnings then education policies can be used as a means of helping the poor to help themselves. If a causal link from education to earnings reflects increases in productivity then educating individuals will help generate economic growth, producing benefits that spill over to more than just the people who get the education. Thus, education has the potential to be a "silver bullet" - a policy that hits many targets at once and has little in the way of negative side effects.

On the face of it, establishing the extent of the impact of education on earnings can be done quite simply. We just need to regress individual earnings on individual schooling levels. If education has a beneficial impact then we should see direct evidence that those with more schooling also earn more. There are several issues which prevent this simple solution from being the final word, but the one that has received the most attention is difficulty in separating true impacts of increased schooling from individual differences in ability. To understand this issue, consider a simple model in which there is one type of productive skill (or human capital). The skill is produced using a combination of schooling and individual ability, where ability is defined as productive characteristics which the individual possesses from birth (as opposed to acquired skills). The produced skill is valued by firms, and worker earned income is calculated by multiplying the amount of the skill a worker possess times the price of the skill. The skill price is determined in the labour market. If we have measures of the amount of the skill, earnings, schooling and ability each person possesses then we can fully characterize how the skill is produced and estimate its return. Knowing the return to the skill is useful for understanding whether the skill is truly productive, while knowing how it is produced allows us to evaluate various policy approaches to increasing the amount of skill in the economy.

In reality, we rarely have measures of either the skill or individual ability. Even these shortcomings are not crippling as long as individuals are randomly assigned to different schooling levels. In that case, a simple regression of earnings on years of schooling will still show the extent to which an increase in schooling causes an increase in earnings. What we would observe in the economy would be the equivalent of an experiment in which we randomly sorted people across schooling levels and then observed their earnings outcomes. Of course, people are not randomly sorted across schooling levels: in an economic model, the choice of a number of years of schooling is a decision made by comparing the costs and benefits of extra investment in schooling. The combination of that non-random sorting across years of schooling with unobserved skill and ability is what generates the greatest problems for figuring out the true causal impact of education on earnings.

To understand the nature of the latter difficulty, consider a simple model of an individual choosing a number of years of schooling. Again, suppose that schooling is useful because it, along with ability, is used in producing a general skill which is valued by employers. Thus, considering education as an investment in human capital, the benefit to an extra year of school can be expressed as a rate of return. The rate of return is calculated by comparing the increase in lifetime earnings from having an extra year of schooling to the earnings the individual could have earned if she did not go to school that extra year plus any direct costs of schooling. This rate of return is expected to decline with added years of schooling in part because with each added year, the earnings the individual is giving up to go to school rises. Thus, individuals will continue to go to school until the return on schooling falls to the same level as the return on the next best available investment opportunity. Now, suppose that part of the cost of acquiring more schooling is a psychic cost arising because people do not like to study. If higher ability people face lower psychic costs then their effective rate of return on schooling is higher than that for low ability people. Then, assuming higher ability people face the same outside investment opportunities as do less able people, that implies that they will choose more years of schooling.[1]

With this model of schooling choice in hand, let us return to our original problem of estimating the causal impact of schooling on earnings. Recall that we assume that both ability and schooling contribute to producing the general skill which is remunerated in the labour market. Thus, earnings should rise with both schooling and ability. However, we generally cannot observe ability. Instead, researchers can often do no more than regress earnings on years of schooling. Our problem, in that case, is that we cannot tell how much of any observed positive correlation between earnings and years of schooling results from a causal impact of schooling on earnings (i.e., the impact of an added year of schooling in terms of creating the general skill times the price firms pay per unit of the general skill) and how much of the correlation reflects the impact of higher ability on earnings. Recall that in our simple schooling choice model, more able people choose more years of schooling. Thus, if we observe higher average earnings for individuals with higher schooling levels that positive correlation may just reflect the fact that more able people are both more likely to get more years of schooling and have higher earnings (because ability is directly productive in generating the general skill). In the extreme, schooling may actually have no causal impact on earnings; it may just be serving as a proxy for ability, which is the true determinant of earnings.

One key approach to trying to disentangle true causality effects of schooling on earnings from effects working through correlations with ability has been to try to find a proxy for ability. If we could identify two people who are identical in every dimension including their ability level but who have different education levels then any observed differences in their earnings would be

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[1] We can get the same results if higher ability people can produce more of the general skill with each added year of schooling than can lower ability people.

attributable to a causal impact of education on earnings.[2] While we cannot observe ability directly, there is a long history of using scores from tests designed to test ability as an extra regressor in the earnings regression. The idea is that people with the same test score can be thought of as having the same ability levels and thus, again, if they have different schooling levels and different earnings then the correlation between the two can be used to pin down the causal effect of schooling on earnings.

Much of the early work (and still some of the best work) using this ability proxy approach was done using US data from a specific sample of army veterans. The sample was contacted as part of the US Current Population Survey in 1964 and, as a result, it contains information on earnings, age and schooling levels. It also contains information from the individual's military records. This includes the number of years of schooling the individual had before entering the military and their score on the Armed Forces Qualification Test (AFQT). The AFQT includes questions on vocabulary, math and spatial relations and is intended as an IQ test adapted for the military.[3] The goal of the test was to ascertain general cognitive abilities. The simple model set out above views productive skills as being generated using ability and schooling inputs. Thus, for ability, one would like a measure of the innate abilities of the individual rather than a measure of skills that may be partly generated by schooling. A score on a test administered, say in the late teens, will almost certainly reflect both innate ability and the contribution of schooling to the individual's skills and test taking prowess. Using such a test score as a proxy for ability will likely "steal" some of the direct schooling effect since higher test scores will partly the impact of schooling. Unfortunately, few datasets contain ability tests administered prior to schooling. However, in the case of this specific dataset, some of the sample

[2] In the simple schooling choice model set out above, the difference in schooling would arise because of differences in the opportunity cost of the schooling investment, ie., because the people face different rates of return on other investments.

[3] One way it was adapted to the military is that it included a section on knowledge about tools.

members obtained extra schooling after leaving the military. Thus, the AFQT score obtained when the individual entered the military can be used to control for skills the individual had before deciding on further schooling investment, including their innate ability. Griliches and Mason(1972) take this approach of focussing on schooling increments after military service, controlling for the AFQT score. Chamberlain(1976) uses the same data and sets out a more thorough accounting of the assumptions needed if one is to claim that the coefficient on the post-military years of schooling in an earnings regression reveals the causal impact of schooling on earnings. In the years since this early work with the Veterans sample, the AFQT has been added to several US datasets. It is often used as a proxy for ability with little regard to questions of the timing of the test and how that timing relates to what the test is actually capturing.

The early work on returns to schooling using AFQT scores both in the Veterans sample and other datasets tended to find a common set of results, summarized in Griliches(1977). Namely, that including the AFQT score in an earnings regression reduced 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.

It is worth noting, as small digression, that another common approach to solving the problem of separating schooling and ability effects points to somewhat similar conclusions. In the discussion to this point, we have taken AFQT as a measure of the ability factor we would like to include in our regressions. An alternative approach is to assume that there is some common unobserved factor determining earnings and schooling (and therefore creating the type of problems we have been discussing) but that tests like the AFQT do not measure it. Not having a direct measure of this unobserved factor does not necessarily cause large problems, however. If we could observe two individuals who we think have the same value for the unobserved factor then we could use differences in their earnings and schooling levels to get an estimate of the causal effect of schooling on earnings without having to obtain a direct measure of the factor. This is the reasoning behind a part of the literature that examines outcomes for sets of twins. If we assume that twins have the same ability levels then we can use differences in earnings and schooling between the twins to determine the impact of schooling on earnings, holding ability constant.[4] One of the best studies using this approach, Ashenfelter and Krueger(1990), supports Griliches conclusion that the ability bias in estimated returns to schooling is small.

One common claim about technological change in the last 20 to 30 years is that it has been skill biased: that is it ultimately results in an increase in demand for more versus less skilled workers (e.g., Berman, Bound and Griliches(199x)). If that is true, one would expect to see the return on ability increase over time. Murnane, Willett and Levy(1995) find increased returns to both an ability measure and schooling over time. The data they use come from two US surveys, one for a sample of individuals who graduated from high school in 1972 and one for a sample who graduated high school in 1980. Their measure of cognitive ability is the student's score on a math test that is intended to measure mastery of elementary mathematical concepts such as working with fractions. The earnings measure relates to earned income 6 years after high school graduation in each case. Their key findings are threefold: 1) returns to schooling have increased over time (increasing from .022 to .044 for males when the ability measure is not included in the regression); 2) including the ability (math test score) in the regression cuts the coefficient on education approximately in half, regardless of whether the earlier or later sample of high school graduates is being examined; 3) the return to ability has almost tripled for males and doubled for females. The first result fits with findings in other papers that returns to education increased substantially in the US in this time period. The second result, in contrast to what was found in the work surveyed by Griliches(1977), indicates that ability bias in standardly

[4] Of course, then one needs to specify why two otherwise identical individuals chose different schooling levels and whether the underlying choice mechanism implies biases of its own.

estimated returns to schooling is substantial. This may suggest that the ability measure in this paper is substantially different from IQ type tests. In particular, it attempts to test direct math skills and includes attempts to test "students' skill in following directions" (Murnane et. al.(1995), p.253). This may mean that the "ability" score in this case is closer to what is being measured in the IALS, i.e., literacy or numeracy skills. We will return to this point below. The third result says that earlier papers may have been correct in finding that returns to basic cognitive abilities or skills were small in the 1970s or earlier but that these returns have increased substantially over time.

3) A Simple Model of Literacy Skills and Earnings

We are now in a position to examine the direct impact of adult literacy on earnings and, more importantly, understand estimates of this relationship in the context of the wider literature on returns to human capital investment in general and schooling in particular. One of my contentions in discussing recent studies of literacy and earnings is that what is measured as literacy skills in surveys such as the IALS is fundamentally different from what was being measured in tests such as the AFQT. To understand why that distinction is important, we need a simple model of how ability, earnings, schooling and literacy skills are related. This model will build on the model of earnings, ability and schooling discussed in the previous section. The rest of the discussion in this section is set out in terms of straightforward and somewhat boring algebra. Uninterested readers can skip the remainder of this section as long as they first recognize the following main points. First, cognitive abilities and cognitive skills need not be the same thing. I view the latter as being produced by the former. Moreover, the coefficients on an ability measure and a skill measure need not be the same: it may well be the case that the coefficient on an ability measure is much smaller than that on a skill measure. Second, the extent to which the coefficient on a years of schooling variable in an earnings regression drops when a literacy measure is introduced into the regression provides a measure of the extent to which regularly measured returns to schooling reflect the impact of schooling in producing literacy skills. If the coefficient on schooling drops to zero, for example, that would imply that schooling is only useful in producing cognitive skills.

Suppose, for the moment, there are three productive skills a worker can possess (rather than the one skill we considered in the earlier section) and workers can possess the skills in varying amounts. A price for each skill is established in the labour market in a manner that depends on how productive the skill is and how big is the supply of the skill. Thus, earnings for an individual are determined by the following equation:

$$1)\ E_{it} = r_t^1 G_{it}^1 + r_t^2 G_{it}^2 + r_t^3 G_{it}^3$$

where, E_{it} are earnings for individual i in year t, G_{it}^1 is the amount of skill 1 that person i sells in the market in period t, G_{it}^2 is the amount of skill 2 that person i sells in the market in period t, G_{it}^3 is the amount of skill 3 that person i sells in the market in period t, and r_t^1 , r_t^2 and r_t^3 are the prices of skill 1, skill 2, and skill 3, respectively. We might think of skill 1 as corresponding to the type of cognitive skills measured in literacy tests. Skill 2 might correspond to other cognitive skills, not captured in the tests, such as skills obtained from learning tasks on the job, and skill 3 might correspond to non-cognitive skills such as getting along with others, again not measured in literacy tests. Then, if we know the value of r_t^1 , we know how highly literacy skills are valued.

The three skills are produced, potentially, from a combination of individual ability, what is learned at school, and what is learned through work (often, acquiring skills during periods of formal schooling is called schooling while acquiring skills in the labour market is called training). We will allow for the possibility that "ability" is multi-dimensional. That is, an individual can be born with high levels of ability related to the type of cognitive skills reflected in literacy tests and either high or low non-cognitive abilities. Studies of scores from tests attempting to test cognitive skills point to the existence of a single common factor, often called “g”, underlying the test results. This may suggest a single cognitive ability factor. There is little evidence to this point, however, that there is a single non-cognitive ability or skill (e.g., Bowles et. al.(2001)). We will assume, as a result, that there are three ability factors, represented in a 3x1 vector, a_i, for person i. For the moment, we will assume that each of the ability factors can contribute to producing each skill. Thus, a non-cognitive ability such as persistence might help in producing cognitive skills by helping individuals make greater use of their cognitive abilities. Given these assumptions, the amount of skill 1 the person possesses in period t can be written as,

$$2)\ G_{it}^1 = \beta_0^1 + \beta_1^1 S_i + \beta_2^1 x_{it} + \gamma^1 a_i$$

where, S_i is the amount of schooling individual i obtains, x_{it} is the amount of labour market experience individual i has by time t (where experience is seen as a proxy for training), and a_i is defined above. In this representation, $\beta_0{}^1$, $\beta_1{}^1$, and $\beta_2{}^1$ are scalar parameters while γ^1 is a 1x3 vector of parameters reflecting the effects of the various abilities on the amount of the skill the individual possesses. The amounts of the other two skills an individual possesses are generated from similar production functions.

Given functions, such as 2), showing how skills are generated, we can rewrite the earnings an individual has as a function of schooling and experience:

$$\begin{aligned} 3)\ E_{it} = {} & r_t^1 (\beta_0^1 + \beta_1^1 S_i + \beta_2^1 x_{it} + \gamma^1 a_i) \\ & + r_t^2 (\beta_0^2 + \beta_1^2 S_i + \beta_2^2 x_{it} + \gamma^2 a_i) \\ & + r_t^3 (\beta_0^3 + \beta_1^3 S_i + \beta_2^3 x_{it} + \gamma^3 a_i) \end{aligned}$$

which, gathering terms, yields,

$$\begin{aligned} 4)\ E_{it} = {} & (r_t^1 \beta_0^1 + r_t^2 \beta_0^2 + r_t^3 \beta_0^3) + (r_t^1 \beta_1^1 + r_t^2 \beta_1^2 + r_t^3 \beta_1^3) S_i \\ & + (r_t^1 \beta_2^1 + r_t^2 \beta_2^2 + r_t^3 \beta_2^3) x_{it} + (r_t^1 \gamma^1 + r_t^2 \gamma^2 + r_t^3 \gamma^3) a_i \end{aligned}$$

This is just the standard Mincer earnings regression, which is usually written as:

$$5)\ E_{it} = \alpha_0 + \alpha_1 S_i + \alpha_2 x_{it} + u_{it}$$

As discussed above, the goal in much of the existing economics literature is to obtain a consistent estimate for α_1. A key concern in estimating α_1 was correlation between the ability factors (the a's in equations 2, 3 and 4) and schooling, S. This might arise because more able people face lower psychological costs of schooling. One response, we saw, was to try to obtain measures of the ability factors and include them in the regression. In almost all cases, the proxy for ability relates only to cognitive skills. If we assign the first element of the ability vector to be the cognitive ability and write it as a_{1i} then this would yield a regression given by,

$$\begin{aligned} 6)\ E_{it} = {} & (r_t^1 \gamma_1^1 + r_t^2 \gamma_1^2 + r_t^3 \gamma_1^3)\, a_{1i} + (r_t^1 \beta_0^1 + r_t^2 \beta_0^2 + r_t^3 \beta_0^3) + (r_t^1 \beta_1^1 + r_t^2 \beta_1^2 + r_t^3 \beta_1^3)\, S_i \\ & + (r_t^1 \beta_2^1 + r_t^2 \beta_2^2 + r_t^3 \beta_2^3)\, x_{it} + (r_t^1 \gamma_{n1}^1 + r_t^2 \gamma_{n1}^2 + r_t^3 \gamma_{n1}^3)\, a_{n1i} \end{aligned}$$

where $\gamma_1^{\,1}$ is the first element of γ^1, $\gamma_{n1}^{\,1}$ is a 2x1 vector containing the remaining elements of γ^1, $\gamma_1^{\,2}$, $\gamma_1^{\,3}$, $\gamma_{n1}^{\,2}$ and $\gamma_{n1}^{\,3}$ are defined analogously, and a_{n1i} contains the second and third elements of the a_i vector. Writing this in a simpler form, we get,

$$7)\ E_{it} = \delta_1 a_{1i} + \alpha_0 + \alpha_1 S_i + \alpha_2 x_{it} + u_{it}$$

The first attempts at estimating equation 7) yielded estimates of α_1 that were little different from estimates obtained without including ability measures in the regression. Furthermore, the coefficient on the ability measure itself was small.

Our goals are different. We are interested in the generation of and returns to literacy skills. If we label skill 1 as literacy skills then we are interested in estimating the β coefficients in equation 2) (i.e., the parameters telling us about how the literacy skills are generated) and $r_t^{\,1}$ (the return to literacy skills). We can do both of these if we have a measure of $G_{it}^{\,1}$. Our claim is that we have such as measure - the test score results from the IALS. Using G_{it}^1, our earnings regression becomes,

$$8)\ E_{it} = r_t^1 G_{it}^1 + (r_t^2 \beta_0^2 + r_t^3 \beta_0^3) + (r_t^2 \beta_1^2 + r_t^3 \beta_1^3) S_i + (r_t^2 \beta_2^2 + r_t^3 \beta_2^3) x_{it} + (r_t^2 \gamma^2 + r_t^3 \gamma^3) a_i$$

Thus, the coefficient on G_{it}^1 will give us an estimate of r_t^1 while the coefficients on S and x will now reflect a combination of how schooling and experience, respectively, contribute to the production of the other two skills and the price of those skills. The error term in the regression now reflects the effect of abilities in producing the other two skills.

How would our estimate of the coefficient on G_{it}^1 differ from what was measured in earlier papers? Given the systems we have established, the coefficient on G_{it}^1 in equation 8) will equal r_t^1 while the coefficient on a_{1i} in equation 7) will reflect a combination of the various skill prices and the impact of cognitive ability in producing all three types of skills.[5] The two coefficients will be identical only if: 1) cognitive ability is not useful in producing non-cognitive skills; and 2) we redefine a_{1i} so that one extra unit of cognitive ability translates into one extra unit of G_{it}^1 (i.e., $\gamma_1^1 = 1$). The second of these conditions is just an innocuous normalization (given we are willing to assume that $\gamma_1^1 > 0$) because it simply requires readjusting units on a variable we do not observe. Whether we should think of cognitive abilities being productive in generating non-cognitive skills is simply uncertain. One could imagine that cognitive abilities are uncorrelated with traits such as persistence and willingness to compromise. On the other hand, more intelligent (i.e., higher cognitive ability) individuals may be better able to see and understand their impact on others and adjust their behaviour accordingly. It would be very useful to delve into psychological literatures on measuring cognitive and non-cognitive traits and their

[5] In both equations, biases will be introduced if the various ability factors are correlated. However, the nature of the correlations between the included variables and the ability factors remaining in the error term will differ, leading to potentially different biases.

correlations. To this point, I have not done this.

If the coefficients on G_{it}^1 in equation 8) and a_{1i} in equation 7) are identical then, according to our framework, they both represent r_t^1. To the extent this is true, we can turn to earlier results in papers trying to control for ability and use them as a basis for discussing trends in returns to literacy. In particular, given the results discussed in the previous section, one would argue that returns to literacy have increased over the past two decades. If the coefficients are not analytically identical then the increased size of the coefficient on a_{1i} over time may still represent an increase in r_t^1 but it may also reflect increases in r_t^2 and/or r_t^3, and/or increased efficacy of cognitive abilities in producing any or all of the skills that are ultimately remunerated in the labour market. That is, we cannot say for certain that the return to literacy skills have increased in the last 30 years but we can say that cognitive abilities have become more important in earnings generation. It is interesting to consider this result in combination with the well-researched observation that average IQ scores have increased substantially across several generations in many Western economies. Assuming that successive generations have not reached average intelligence levels that would have be considered genius only a generation before, this implies that the attributes measured by IQ type tests are not solely inherent abilities. To some extent the skills used in answering IQ tests are acquired. This, in turn, means that a sharp distinction between IQ tests and literacy tests may be artificial: IQ tests may be more skewed toward measuring inherent ability and literacy tests may be more skewed toward measuring cognitive skills, but they probably have substantial overlap.

The outcome of the discussion in this section is that results from earlier papers using IQ type measures of cognitive abilities do not allow us to estimate the returns to and determinants of literacy on earnings. In the next section, we will describe Canadian data that does allow us to examine these issues and in subsequent sections we will outline results from studies that have used that data.

4) International Adult Literacy Survey Data

The International Adult Literacy Survey (IALS) is a fascinating survey carried out in over twenty different countries between 1994 and 1998. The IALS attempted to measure literacy in three broad areas: Prose, Document and Quantitative. Perhaps of most importance for our discussion, the IALS did not attempt to just measure abilities to read and perform math but tried to assess capabilities in applying skills to problem solving in everyday life. Thus, the Prose questions in the survey 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 Quantitative 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 table. Thus, the questions are related to implementation of skills in the real world and are intended not just to elicit abilities in answering current questions but adaptability to answering further questions in other contexts. As described by Statistics Canada,

"... the IALS does not challenge the reality that most adults can in fact read, but it does question whether they can read well enough to get the correct answers on test items that represent the range of difficulty foudn in task that they encounter in their daily lives." (Statistics Canada, 1996)

Thus, in contrast to earlier tests such as the AFQT in the US, the IALS is not trying to measure innate ability but rather literacy skills applicable in daily life. In this sense, the measures from the IALS can be seen as attempts to capture the skills we represented by G_{it}^{1}. It is worth reemphasizing that these skills are essentially cognitive in nature. We will return to discussing other (non-cognitive) skills below.

An early Statistics Canada evaluation of the 1994 IALS for Canada revealed some interesting patterns (Statistics Canada(1996)). Among six OECD countries and focussing on individuals over age 16, Canada placed in the middle to upper part of the pack. On both the Prose and Document scales it had higher proportions of respondents in the top assessment category than Germany, the US, the Netherlands and Switzerland but lower than Sweden. But it also had a relatively large proportion in the bottom-most category. In Quantitative skills, Canada ranked about the same as most of the countries but again worse than Sweden. Thus, existing levels of adult literacy are neither exceptionally high nor exceptionally low relative to other OECD countries. Canada appears to have slightly better results than our main trading partner, the US, but substantially worse results than Sweden.

Within Canada, the study finds a strong correlation between schooling and literacy. Adults who do not have an secondary education fall mostly in the bottom literacy category with few placing in the top category. The university educated reveal the inverse pattern. The results for the Quantitative scale are reproduced in Table 1. These patterns fit well with a pattern in which increased education generates increased literacy scores. However, the correlations depicted in Table 1 could arise if those with greater literacy skills either choose to get more schooling or are able to pass more hurdles and hence go farther in the schooling system. Alternatively, the positive correlation could also reflect the impact of some common underlying factor (such as cognitive ability) on both schooling attainment and literacy outcomes rather than the direct production of literacy skills through schooling. For the moment, we will continue to assume that the correlation arises from the productive effects of schooling but we return to discuss more on this issue below.

The results in the Canadian version of the IALS show mixed results by gender. Women score higher on the Prose questions but men score slightly higher on the Document and

Quantitative questions. The results by age group indicate that older individuals, and particularly those who got their schooling before WWII, have substantially lower literacy scores. This fits with differential patterns in schooling across generations.

5) Results from Studies Examining the Relationship Between Earnings and Literacy

The main published work on labour market impacts of literacy and numeracy in Canada is found in Charette and Meng(1998). They use the precursor to the IALS, the Literacy Skills Used in Daily Activities (LSUDA) survey, which contains similar literacy and numeracy test scores to the IALS. The main differences between the two datasets, for our purposes, are that the LSUDA does not permit as fine a distinction in literacy levels among those with high levels and that the LSUDA asked about total income rather than earnings. Charette and Meng use the LSUDA to investigate the determinants of literacy. They find impacts of family background, province of residence, age and schooling but, based on specifications in which they instrument for schooling, conclude that family background variables affect literacy acquisition mainly through their effect on schooling outcomes. Their estimates of the impact of literacy on income indicate that including literacy and numeracy scores in the income regression reduces the coefficient on schooling for males by about 20% for males but actually increases the schooling coefficient for females. The latter result may reflect the dependent variable: literacy may have different impacts on the relationship between schooling and income than on the relationship between schooling and earnings. With women being likely to work fewer hours, the non-work income relationships may be more important for men than women. For both men and women, Charette and Meng find substantial effects of literacy and numeracy test scores on income.

Our main discussion will centre around results found in Green and Riddell(2001, 2001a). These papers are based on the 1994 Canadian version of the IALS. The full sample size is 5660 individuals over the age of 16. We exclude respondents who did not work during the 12 months prior to the survey, those who report their status as student or retired, and individuals who reported working part time and going to school during the previous year. After eliminating observations for whom there was no reported earnings and/or years of education, we were left with a sample of 2190 observations. The survey is based on the Labour Force Survey (LFS) sample frame and we use the LFS weights in our analysis. In Green and Riddell(2001), we use annual earnings from both paid and self-employment as our earnings measure. Given our discussion above, we would like a measure of remuneration that comes as close as possible to the sum of skill prices times the skills used. We would prefer to avoid selection issues that might arise from variability in annual earnings that are associated with differences between part time and full time status. For this reason, in Green and Riddell (2001a), we use annual paid employment earnings for full-year/full-time workers only. In the latter paper, we also perform separate analyses for males and females.

The key first question we asked was whether the IALS data could replicate standard patterns, in terms of returns to schooling and experience, from the huge number of previous studies that have estimated earnings regressons. To check this, in both studies we estimated variants of equation 5), above, with the experience profile allowed to be non-linear. Green and Riddell(2001), using annual earnings for all workers with males and females pooled together, show a coefficient on a years of schooling variable of .083. This is well within the normal range of estimates obtained for regressions of this type (see Card(1999)). The coefficient on constructed years of experience (.046) is also well within a standard range. Using annual earnings for full year full time workers, Green and Riddell (2001a) find coefficients of .048 for males and .12 for females. This pattern of higher returns to schooling for females is also common in the previous literature. Table 2 recreates some of the findings from Green and Riddell (2001a).

Having established that the IALS data gives standard results from estimating equation 5), we can turn to our main topic of interest: how literacy skills are remunerated and how that interacts with schooling. We tried working with the Document, Prose and Quantitative test scores separately but obtained results indicating strong collinearity among them.[6] 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 in the three scores. This fits with the idea first promoted by Spearman in the early 1900's that all cognitive abilities were reflections of “g”, or the single factor, general ability.

We estimated the direct effect of literacy on earnings, what we called the literacy skill price, r_t^1, in section 3), by estimating equation 8), above (i.e., a regression with earnings as the dependent variable and years of schooling, experience and the average literacy score as covariates). The direct effect of literacy on earnings is captured in the coefficient on the average IALS score in column 2 for men and column 4 for women. For men, testing suggested that the relationship between earnings and literacy is a simple linear one, while for women a quadratic in the average score fit the data better. In both cases, the impact of literacy is sizeable. For men, a 10 unit increase in the average literacy score generates earnings increases equivalent to those that could be obtained from one extra year of schooling. A 10 unit increase is only about 1/3 of a standard deviation of the average IALS score distribution and is the increase one would need to move from the 10th to the 25th percentile in that distribution. For women, a 10 unit increase in literacy increases earnings by slightly more than the equivalent of a year of schooling, though the returns to both schooling and literacy are substantially larger than for males. Thus, for both genders, the return to literacy, r_t^1, is both statistically significantly different from zero and economically substantial. The cognitive skills captured in literacy tests are strongly rewarded in

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[6]The R^2 for the regression changed very little whether we were dealing with one of the scores or all three together and the standard errors on the coefficients associated with the test scores became quite large when all three scores were included in the earnings regression. 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. (Green and Riddell (2001).

the market.

Literacy skills are far from the sole determinant of earnings, however. As we discussed in section 3), if schooling continues to be a significant determinant of earnings even after including a literacy measure in the regression, this indicates that there are other skills, not captured by the literacy tests, which are generated in schools and are remunerated in the labour market. As seen by comparing results in columns 1 and 2 of Table 2, for men, including the average IALS score caused a drop in the coefficient on schooling from .048 to .027, or by 44%. For women, the results in columns 4 and 5 of Table 2 indicate that including the literacy score reduces the schooling coefficient from .12 to .078, a drop of approximately 35%. Similarly, when attention is not restricted to full-year/full-time workers, the schooling coefficient drops by 37% when the average literacy score is added to the equation (Green and Riddell(2001)). From this we can glean two conclusions. First, a substantial portion of the regularly estimated returns to schooling can be accounted for by the literacy skills generated in school. Second, since schooling continues to enter with a statistically significant effect of substantial size, we can state clearly that literacy skills are not the only productive skill generated in schools.[7] Indeed, between half and two-thirds of the schooling impact measured using regressions such as 5) is associated with non-literacy skills. These results are not very different from those in Murnane et. al.(1995), who find that the coefficient on their schooling variable in an earnings regression declines by 43% when they bring math test scores into the regression as an extra covariate.

The coefficients on the quartic in experience perform strikingly differently from those on schooling. For both genders (but for men in particular), the coefficients on the experience variables change very little when the average IALS score is added to the regression. Returning to equations 4) and 8), the only difference between the coefficients on experience when the literacy

[7] All of this discussion assumes that the literacy tests fully capture cognitive skills apart from a measurement error. Further, any measurement error in this measure of cognitive skills is not correlated with schooling.

score is and is not included is the term $r_t^1\beta_2^1$. This represents the effect of experience in helping to generate literacy skills (β_2^1) times the price per unit of the literacy skill. Given that the coefficient on the literacy score (which we interpret as equalling r_t^1) is non-zero, the coefficient on experience will remain unchanged with the inclusion of the literacy score only if $\beta_2^1 = 0$, i.e., if labour market experience plays no role in generating literacy skills. We return to this point below. Interestingly, Murnane et. al. (1995), using math test scores as the measure of cognitive skills, get the same result (though they do not make note of it): in their case, too, the coefficient on experience does not change with the inclusion of the test score.

In Green and Riddell(2001a), we also ran quantile regressions using the covariates as set out in equation 8), for the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles. A very striking result from this analysis for men is the fact that the IALS score has the virtually exactly the same coefficient at each of the percentiles we studied. This has interesting implications for the skill production and earnings generation model set out in section 3). In particular, it implies that literacy skills and the other, unmeasured skills that have been relegated to the disturbance term in equation 8) do not interact in the production process. If they did interact then one would find that, for example, the IALS score had a larger coefficient at the 75^{th} than the 25^{th} percentile. This result is reinforced by the fact that in specifications where we allowed for interactions between schooling and literacy score, we found no statistically significant interaction effect. On the other hand, the interaction of the literacy score and experience is statistically significant and negative. We return to an interpretation of these results below.

We can use the observed literacy score to examine how literacy skills are generated as well as how they affect labour market outcomes. In Table 3, we present separate regressions of literacy score levels on schooling, parental education, years of labour market experience, and experience squared. The results in Table 3 show a very strong effect of schooling on literacy, with an extra year of schooling associated with a 6.45 point increase in the average literacy score for males and a 9.49 increase for females. In contrast, and in keeping with what we found in the earnings regressions, experience has an economically small and statistically insignificant effect on literacy for both males and females. Father's education has generally small and statistically insignificant effects on literacy, with the sole exception that having a father with a university education reduces literacy relative to the base case of having a father with only a primary school education for females. This latter result is somewhat perplexing. In contrast to father's education, mother's schooling has substantial and generally statistically significant effects on schooling. Interestingly, these impacts are larger for males and the largest impacts are not for individuals with mothers who went to university but for those whose mothers had some post-secondary education. Overall these results contradict Charette and Meng(1998)'s claim that family background variable effects fade to unimportance once years of education are included. The results indicate the schooling and mother's education are important determinants of literacy while father's education and labour market experience are not.

A final empirical issue that requires attention is the potential endogeneity of schooling in both the earnings and literacy regressions. If people with higher ability values face higher returns to schooling or lower psychic costs of acquiring schooling then the coefficient on years of school will partly pick up the causative effect of schooling on earnings and partly reflect the fact that people with more schooling are more able. Similarly, the schooling coefficient in the literacy equation could partly capture ability differences across individuals with different schooling levels and/or the idea that one needs more literacy skills to get to higher levels of education. Finally, literacy itself may be correlated with the omitted ability terms in equation 8), to the extent that various types of ability are correlated. Thus, the literacy variable, too, raises potential endogeneity concerns. In both Green and Riddell(2001 and 2001a), we attempt to address this issue using instrumental variables approaches. To instrument for years of schooling we use IALS variables detailing the reason an individual stopped his or her schooling as well as parental education variables. We instrument for literacy in the earnings regression using an indicator for whether individuals first language spoken was a language other than the language of the IALS survey, controlling for current language fluency. The results depend on the exact set of instruments we use but in each case, instrumenting reduces the coefficient on education substantially. For males, in fact, it virtually reduces the schooling coefficient to zero. Once instrumenting is carried out we find either small changes in the coefficient on literacy or substantial increases, depending on the exact procedure used. In all cases, the result that the coefficients associated with experience are unchanged with the inclusion of the literacy score variable remains. We are not fully comfortable with the instrumental variables results and, hence, only mention them in passing. However, they point toward a conclusion that literacy has significant causal impacts on earnings.

6) Interpreting Empirical Patterns Linking Earnings and Literacy

Based on the estimated relationships between earnings, schooling, literacy and experience, we can draw several conclusions about the importance of literacy in the modern Canadian economy. We take the stance that if literacy is important in the economy then it will show up in the way an individual is remunerated. The key finding from work with the IALS data is that there is a very substantial return to literacy in the Canadian labour market. An increase in an individual's literacy score equivalent to about 1/3 of a standard deviation in the literacy score distribution is associated with the same size increase in earnings as one extra year of schooling. Second, these measured effects are larger for females than males. Third, it appears that a substantial part (at least 1/3) of typical estimates of the impact of schooling on earnings stem from the effect of schooling in raising literacy. Fourth, there is no evidence that added years of experience in the labour market increases literacy. That is, individuals do not appear to acquire even the type of literacy skills measured in the IALS - skills required in performing every day work tasks - just by spending time in the labour market. Individuals have to take part in active programmes to acquire additional literacy skills. In this sense, increasing adult literacy requires funding literacy training, not just relying on on-the-job type training to both increase skills needed on the specific job and more general literacy skills. This may fit with traditional analyses that claim that firms will not help invest in general skills (such as literacy) because of fears of poaching of the newly trained worker by other firms. Fifth, Green and Riddell(2001a) argue that the combination of the similarity in the impact of literacy on all quantiles in the earnings distribution, the lack of a measurable interaction between literacy and schooling in the earnings regression, and the existence of a significant interaction between literacy and experience in the earnings regression point to a production technology with at least three major skill inputs: 1) literacy skills produced using schooling and ability but not labour market experience; 2) a set of skills not captured in literacy tests that may be generated using schooling and ability and that do not interact with literacy skills in production (i.e, having more literacy skills does not enhance the productivity of this second set of skills) - these might be non-cognitive skills; 3) a set of skill that are again not captured by literacy tests but are produced using experience and, perhaps, ability. The latter set of skills, which might be skills in how to better perform a set of tasks, do interact with literacy in production. For males, these latter skills appear to be substitutes for literacy skills in production. That is, as males get more experience and more of the skills generated through experience, they have less need for literacy skills. For females, on the other hand these skills appear to complements with literacy skills in production.

We have established that literacy skills are important in the Canadian labour market. However, we have not yet tried to evaluate how important these skills are relative to the other skills, the effects of which we observe only indirectly. Even with the literacy scores included, the adjusted R^2's in regressions using the IALS are at most .52. This is a relatively large R^2 for a cross-sectional earnings regression but it still indicates that 50% of the variation in earnings in our sample is left unaccounted for by our covariates. If the cognitive skills captured by literacy tests were the only factors rewarded in the labour market, we would expect to see much higher R^2's once the literacy score was included. Further, the coefficient on schooling in earnings regression drops substantially but still retains at least 50% of its size when literacy scores are brought into the regression. This suggests that schooling is productive in ways other than just generating literacy skills. Thus, these results, as with those in many other studies, point to the importance of non-cognitive skills in the labour market.

In the last few years, there has been a burgeoning literature on the importance of non-cognitive skills in economics as economists widen their vision to take in factors that have long been studied by sociologists and psychologists. Bowles and Gintis(2000) cite evidence from two surveys on the importance of non-cognitive skills for employers. The first is a 1998 survey of employers by the US Bureau of the Census which asked employers about what they looked for in new, non-supervisory workers. The list of potential responses included years of schooling and industry specific skill credentials but the two ranked as most important by far were "attitude" and "communications skills". The second is from a survey of British employers. In that survey, employers who reported a skill shortage were asked to specify the cause of the shortage. Approximately 43% replied that the problem stemmed from lack of technical skills but 62% reported the problem stemmed from workers with "poor attitude, motivation or personality" (Green et. al.(1998). Heckman and Rubinstein(2001) report on estimations of earnings regressions using US data and including a measure of General Educational Development (GED) testing programme results. Under the GED, high school drop-outs can take a series of tests to find out if they are the academic equivalents of high school graduates. If they pass the tests, they are awarded a diploma equivalent. Yet in regressions including both indicators for standard high school completion and GED equivalents, holders of the GED equivalents earn more than other high school drop-outs but less than high school graduates. Heckman and Rubinstein argue that this is consistent with the GED holder having more cognitive skills than other drop-outs (enough to make them the functional equivalents of high school graduates) but fewer non-cognitive skills than high school graduates. That is, high school graduates and GED holders are measurably identical on literacy type tests but high school graduates by the very fact that they stayed and completed high school show greater persistence. This supports earlier work in Cawley et. al.

(1996) that also indicates that cognitive abilities are a relatively minor predictor of outcomes such as earnings.

Using evidence such as that just cited, Bowles and Gintis(2000) go on to argue that the coefficient on schooling in an earnings regression such as 8), which includes a literacy measure, captures the effect of schooling in producing non-cognitive skills combined with the return those skills in the labour market. They cite a series of papers in which the reduction in the schooling coefficient once a measure of cognitive ability is included is on the order of 20%. This is less than the reduction we found using the IALS but the studies cited by Bowles and Gintis appear to generally be using ability tests such as the AFQT. We argued above that these tests may not capture final literacy skills as much as ability inputs to creating those skills. In any case, whether using our results or those set out by Bowles and Gintis, non-cognitive skills may account for between 55% and 80% of measured returns to schooling. Thus, Bowles and Gintis' answer to the question they set out in their title ("Does Schooling Raise Earnings by Making People Smarter?")
is mostly, no: the majority of the schooling impact is through endowing individuals with non-cognitive, productive traits such as persistence, willingness to follow orders, etc. It should be mentioned that not all of these traits are necessarily viewed as positive in society as a whole and Bowles et. al. (2001) cite evidence that traits such as aggressiveness are positively rewarded for males but negatively rewarded for females.

7) Conclusion

My goal in this paper was to examine the importance of literacy skills in the Canadian economy. The key assumption in my approach has been that we can assess that importance of those skills by looking at their impact on individual earnings. If earnings reflect, in part, the productivity of the skills individuals possess then larger impacts of literacy skills on earnings indicate greater importance for literacy skills in production in the current Canadian economy. In order to assess the importance of literacy skills, we needed to set out a framework for thinking about how they relate to production and earnings. Most importantly, we needed a framework that would allow us to link results using recent datasets that include literacy test scores to a longstanding literature attempting to assess the extent of ability biases in measuring the impact of schooling on earnings. The framework set out in section 3 suggests that it is important to distinguish between measured literacy skills and underlying abilities used in generating those skills. The coefficients on measures of literacy skills appear to be larger than those on ability measures.

The key findings with respect to the importance of literacy skills are as follows. First, literacy skills are very important determinants of earnings, with an increase in an individual's literacy score equivalent to 1/3 of the standard deviation of literacy scores in the population being associated with the same size increase in earnings as one extra year of schooling. Further, between 1/3 and ½ of the effect of schooling on earnings appears to arise because of the impact of schooling in generating greater literacy. Second, a review of the earlier literature indicates that literacy has been becoming more important as a determinant of earnings over the last three decades. Third, even though literacy skills are important, the fact that we can typically explain less than half the variation in earnings with measured covariates and the fact that the coefficient on schooling does not fall to zero once literacy measures are included points to the existence and importance of skills not captured in literacy tests - non-cognitive skills. Interestingly, our regression results indicate that these non-cognitive skills do not interact with cognitive skills in production. That is, having more of both types of skills increases earnings (i.e, both enhance productivity in our model) but having more non-cognitive skills does not enhance the productivity of the cognitive skills an individual has (or vice versa), in general. This is an intriguing finding that contradicts models that argue that non-cognitive skills are useful to the extent they enhance the ability of individuals to use their cognitive skills. It suggests that non-cognitive skills are productive in their own right.

We also looked briefly at the generation of literacy skills. Our main findings are that schooling and parental education are important in generating literacy skills but that labour market experience is not. Thus, increasing the literacy level of the Canadian workforce would require direct, active policies rather than just re-enforcing standard on-the-job training.

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Table 1
IALS Respondents by Literacy Level and Education (Percentages)
Canada: 1994

Highest Level of Education	Quantitative Scale (Levels)			
	1	2	3	4/5
Less Than Grade 8	91	8	-	-
Completed Primary School	61	25	14	-
Some Secondary School	26	41	26	7
Secondary School Graduate	11	33	41	16
Community College Grad.	7	22	46	25
University Graduate	-	5	33	60

Source: Statistics Canada(1996), Table 1.4

Table 2
Log Annual Earnings Mean Regressions: Full Year/Full Time Workers

Variables	Males	Males	Males	Females	Females	Females
Years of Education	.048* (.0053)	.027* (.0058)	.028* (.0058)	.12* (.0062)	.078* (.0073)	.078* (.0073)
Average IALS Score	-	.0028* (.00037)	.0048* (.00067)	-	.011* (.0024)	.0075* (.0029)
Average IALS Score Squared	-	-	-	-	-.000012* (.0000042)	-.000009* (.000045)
Experience* Score	-	-	-.00010* (.000029)	-	-	.00008* (.00004
Experience	.13* (.020)	.13* (.019)	.16* (.020)	.089* (.025)	.078* (.023)	.05+ (.027)
Experience Squared	-.0059* (.0015)	-.0057* (.0014)	-.0053* (.0014)	-.0033+ (.0018)	-.0025 (.0017)	-.0024 (.0016)
Experience Cubed	.00012* (.000042)	.00012* (.000040)	.00011* (.000040)	.00004 (.00005)	.000024 (.000046)	.00003 (.00005)
Experience to Fourth /100	-.00010* (.000039)	-.00011* (.000037)	-.000093* (.000037)	-.000009 (.000042)	-.000001 (.000039)	-.000004 (.00004)
Rural	-.005 (.054)	-.014 (.049)	-.012 (.049)	.025 (.061)	-.081 (.057)	-.080 (.057)
Constant	8.86* (.11)	8.31* (.13)	7.68* (.22)	7.83* (.14)	6.28* (.34)	7.03* (.51)
Adjusted R^2	.32	.38	.39	.45	.53	.54

Notes: Standard errors in parentheses. * corresponds to the coefficient being statistically significantly different from zero at the 5% significance level. + corresponds to the coefficient being statistically significantly different from zero at the 10% significance level. Source: Green and Riddell (2001a)

Table 3
Average IALS Score Regressions

Variables	Males	Females
Years of Education	6.45 (.59)*	9.49 (.63)*
Experience	-.053 (2.00)	2.36 (2.27)
Experience Squared	.095 (.15)	-.18 (.17)
Experience Cubed	-.0047 (.0042)	.0039 (.0045)
Experience to the Fourth	.000052 (.000039)	-.000026 (.000038)
Father's Education - Some High School	-8.06 (6.90)	4.28 (5.45)
Father's Education - Completed High School	-4.94 (7.57)	4.88 (6.28)
Father's Education - Post-Secondary	6.11 (10.44)	10.62 (10.22)
Father's Education - University	1.48 (9.15)	-15.65 (7.66)*
Mother's Education - Some High School	39.95 (6.74)*	13.43 (6.66)*
Mother's Education - Completed High School	44.51 (7.56)*	3.15 (7.30)
Mother's Education - Post-Secondary	58.27 (8.79)*	29.16 (9.82)*
Mother's Education - University	30.08 (11.38)*	26.94 (11.83)*
Constant	179.82 (11.57)*	151.67 (12.92)*
Adjusted R-Squared	.39	.43

Notes: Standard errors in parentheses. * corresponds to the coefficient being statistically significantly different from zero at the 5% significance level. + corresponds to the coefficient being statistically significantly different from zero at the 10% significance level. Source: Green and Riddell(2001a)