Adult Literacy, Heterogeneity and Returns to Schooling in Chile

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Abstract: We examine the importance of adult functional literacy skills for individuals using a quantile regression methodology. The inclusion of the direct measure of basic skills reduces the return to schooling by 27 percent, equivalent to two additional years of schooling, while a one standard deviation increase in the score increases earnings by 20 percent. For those who are less skilled, more education contributes little to earnings; rather skills are the key to higher earnings. The non-schooling component of skill is a significant contributor to earnings, but not the component associated with years of schooling.

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1. Introduction

When estimating returns to schooling using a Mincer type earnings function, the disturbance term will capture individual unobservable attributes and effects which, in general, tend to influence the schooling decision, hence resulting in a correlation between schooling and the error term. Cognitive (as well as non-cognitive) ability is such an unobservable; if schooling is endogenous then ordinary least Squares (OLS) estimators of the return to schooling are biased.

The return to investing in education, based on past empirical studies, is known to differ between individuals in different parts of the earnings/ability distribution. For example, evidence from the United States (Ingram and Neumann 2005) shows that over the past decades, individuals with college education but without specific skills experienced the lowest benefits from investing in education. Therefore, individuals lacking in literacy and related skills may not benefit as much from investing in education, compared to individuals better endowed in functional skills; for the latter, skill is expected to interact positively with education resulting in higher benefits from education investments.

When a true measure of ability is an omitted variable in the earnings equation, one of three different approaches have been used in the empirical literature to capture "true" return to education. The first approach uses twins, to arrive at a measure of the causal return to education. For example Ashenfelter and Rouse (1998) and Rouse (1999) using data from the US, have compared the earnings of twins with different educational levels, and reported an estimate of the return to education that is about 30 percent smaller than the OLS estimate.

The second approach uses sources of exogenous variation in educational attainment, such as institutional changes in the schooling system in the form of changes in compulsory schooling laws, abolition of fees, etc, as well as other "natural variations" (i.e., school construction projects) affecting the schooling decision, to estimate a causal return to education effect using instrumental variable estimation. Most of these estimates of the return to education based on "natural experiments" report a higher return to education (rather than a lower one), compared to OLS-based estimates of the return to education (see, for example, Angrist and Krueger 1991; Kane and Rouse 1995; Card 1995; Harmon and Walker 1995; Meghir and Palme 2005; for developing countries, see DuFlo 1998; Patrinos and Sakellariou 2005). The dominant explanation for these seemingly counter-intuitive results is that institutional changes in the school system (such as compulsory schooling laws) affect the schooling decision of a subset of individuals who, otherwise, would not have pursued a higher level of education and not the average individual. Furthermore, individuals affected by such reforms tend to have a higher return to education than the average individual.

The third approach, and also the approach used in this paper, uses achievement test scores reflecting a range of skills (in our case, adult literacy), and employ them as additional controls in the earnings function. One should, however, keep in mind that both schooling and other skills are generated by the same latent ability. Therefore, one has to be aware of the joint causality between schooling and test scores (see Hansen, Heckman and Mullen 2003; Nordin 2008). We use the International Adult Literacy Survey (IALS) data, which contain direct measures of adult literacy and numeracy skills which are

workplace relevant. In particular, the IALS contain labor force information along with scores from a literacy test. The data set includes three scales to measure individuals' literacy levels. These scales relate to prose, document and quantitative literacy. Such data allows the researcher to identify features of earnings determination that are typically only indirectly observed.

Evidence on the relationship between heterogeneity in ability and returns to education using a quantile regressions methodology for Chile can be found in Montenegro (2001), who used 1990-1998 data and found an average return exceeding 10% and strong increasing returns by quantile over many years, as well as in the multi-country study by Patrinos *et al*. (2009), who used 2003 data and reported similar results. Both studies (without controlling for any measure of ability or skill) looked at the pattern of returns by quantile. The concept of ability that is relevant in the above two studies, as well as other studies (for example Arias et. al., 2001), relates to those unobservable, earnings-enhancing, human capital characteristics of an individual rather than measures derived from tests. An increasing pattern of returns was interpreted as evidence in favor of a complementary relationship between ability and education.

The IALS data have been used in several studies, with little evidence on Chile, one of only two countries in the survey outside Europe and North America. Blau and Khan (2001) examined the role of skill in explaining higher wage inequality in the U.S. Leuven *et al*. (2004) used IALS data for 15 countries (including Chile) and explored the hypothesis that wage differentials between skill groups across countries are consistent with a demand and supply framework. Green and Riddell (2003) used the measure of literacy in the IALS dataset to examine the influence of such skills on earnings in

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Canada. They find that these skills contribute significantly to earnings and that cognitive and unobserved skills are both productive but that having more of one skill does not enhance the other's productivity.

Evidence on the effect of adult literacy and other basic skills is scarce and most applications are for Britain and the United States. Ishikawa and Ryan (2002) used data from the National Adult Literacy Survey to examine the relationship between schooling and earnings in the United States. The study finds that, for the most part, it is the substance of learning in school — the accumulated human capital — that counts. It is also found that the strength of the human capital explanation versus the credential explanation of returns to schooling varies by race. Tyler (2004) tested the extent to which the accumulation of basic cognitive skills matter for young dropouts entering today's labor market. Based on a sample of 16-18 year-old dropouts who were administered a math test in the late 1990s, he presented evidence indicating that a standard deviation increase in the test score is associated with 6.5% higher average earnings over the first 3 years in the labor market. Vignoles *et al.* (2011) investigated the importance of basic skills in the U.K. labor market (see also McIntosh and Vignoles 2001) using the new British Cohort Study (BCS) dataset collected in 2004 as a primary data source (and the 1996 IALS as a secondary source, as it does not contain information on ability or skill level at early age). They find that it is the combination of family factors, early schooling and inherent individual characteristics that is a more important determinant of how literate and numerate a person is in adulthood. They also find that the best predictor of adult skill is skill level at primary school and that literacy and numeracy continue to be valued in the U.K. labor market.

2.   Methodology

In the basic Mincerian human-capital model (Mincer 1974), schooling is assumed to be independent of ability, and that the return from schooling investments is equal for all individuals. However, in the contemporary literature it is acknowledged that the return to schooling must be different for different skill levels. Intuitively, an estimate of the average return to schooling probably over-estimates the return for less skilled workers and under-estimates the return to the highly skilled. One should, therefore allow skill to affect the rate of return to schooling investments.

We use the adult literacy score as a measure of basic skill (adult functional literacy and numeracy)[1] to proxy for unobserved effects. We expect that the inclusion of a direct measure of such skills will reduce the estimated education coefficient, so that the coefficient on education then mostly captures the effect of schooling alone, having controlled for a range skills.

Given a distribution of wages, we assume that workers at different parts of the distribution benefit from different types of skills and abilities, including inherent unobserved ability. Less skilled workers predominate in the lower quantiles of the distribution, while the highly skilled predominate in the upper quantiles of the distribution. However, it is hypothesized that adult literacy and numeracy (basic skills) are mostly relevant at lower parts of the earnings distribution, compared to the higher end of the distribution, where higher level skills are more relevant.

A model in which both the measure of skill and its interaction with schooling affect earnings and the skill-specific return to schooling is outlined below (Griliches 1977; Nordin 2008):

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[1] Throughout this paper we will use the terms "basic skills" and "adult literacy" interchangeably.

$$\text{Ln } w_i = \alpha + \beta S_i + \gamma A_i + \varepsilon_i \qquad (1),$$

where w is the hourly wage rate, S is years of schooling completed, A is a measure of skill and ε is an independently distributed error term. Allowing the return to schooling to depend on skill:

$$\text{Ln } w_i = \alpha + \beta(f(A_i))S_i + \gamma A_i + \varepsilon_i \qquad (2).$$

Using the IALS test score (for a description of the data, see next section) as a measure of basic skill (without assuming that it perfectly measures the underlying rage of relevant skills, especially higher order skills):

$$\text{Ln } w_i = \alpha + \beta(f(T_i))S_i + \gamma T_i + \varepsilon_i \qquad (3),$$

where T is the IALS score, an imperfect measure of skill relevant for the workplace[2]. Assuming a linear relationship:

$$f(T_i) = t_0 + t_1 T_i \qquad (4),$$

we obtain the following earnings equation:

$$\text{Ln } w_i = \alpha + t_0 S_i + t_1 T_i S_i + \gamma T_i + \varepsilon_i \qquad (5).$$

Finally, including experience, its square and other covariates:

$$\text{Ln } w_i = \alpha + t_0 S_i + t_1 T_i S_i + \gamma T_i + \exp + \exp^2 + X_i + \varepsilon_i \qquad (6),$$

where X is a vector of other covariates, such as parents' education.

Equation (6) is estimated using both Ordinary Least Squares (OLS) - to obtain estimates of average "return" to schooling - as well as quantile regression in order to observe how the coefficients of years of schooling, cognitive score and the interaction of the two change across the earnings distribution; quantile regression is particularly useful, because it allows the full characterization of the conditional distribution of the dependent

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[2] It is, therefore, clear that the underlying ability variable, A, is now replaced with the test score, a direct measure of adult literacy skills.

variable, rather than the conditional mean only. The quantile regressions methodology (Koenker and Bassett 1978; Buchinsky 1997) allows an investigator to differentiate the contribution of regressors along the distribution of the dependent variable. In particular, the estimation of returns to education entails much more than the fact that, on average, one more year of education results in a certain percent increase in earnings.

3. Data

The International Adult Literacy Survey (IALS) was carried out in 20 countries[3] between 1994 and 1998, a project undertaken by the governments of the countries and three intergovernmental organizations.[4] It is a carefully designed, innovative survey of adult populations, and goes beyond just measuring literacy capabilities to assessing how these capabilities are applied to everyday activities. The IALS was followed by an extensive quality review (see Murray *et al*. 1998) which, after comparing the distribution of the characteristics of the actual and weighted samples, concluded that the actual and weighted samples were comparable to the overall populations of the participating countries. The questionnaire also included questions about labor market status, earnings, education as well as demographic characteristics.

The data includes three scales as measures of literacy skills: prose literacy, document literacy and quantitative literacy, each in the 0-500 range. Prose literacy tests the understanding and use of texts such as editorials, news stories, fiction and poems. Document literacy tests skills required to locate and use information contained in a variety of formats, such as job applications, payroll forms, maps and tables. Quantitative

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[3] The countries are: Belgium, Canada, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, The Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, Sweden, Switzerland, the United Kingdom and the United States of America.
[4] OECD, European Union and UNESCO.

literacy tests skills required in making calculations after locating numbers embedded in printed materials; examples of such calculations include determining the interest on a loan, calculating a tip and balancing a checkbook.

For Chile (year 1998), the survey is representative of 98 percent of the population between the ages of 16 and 65 (it excludes residents of institutions and remote areas) and the total number of respondents was 3,583. A four-stage stratified sample was used and stratification was performed according to region and type (urban/rural). As is the case for the rest of the IALS country data, in the Chilean data the three skills are very highly correlated. Consequently, the average of the three scores will be used in the analysis as an aggregate IALS score measure (see also Blau and Khan 2001; Devroye and Freeman 2001; Leuven *et al*. 2004).

As is the case with the other countries in the IALS datasets, for Chile as well, the relation between skill level and years of schooling is positive. However, the slope of the skill-schooling profile is less steep compared to all but three other countries – Germany, the Netherlands and Sweden – while the slope is steepest in the Czech Republic, the United States, Slovenia and Canada (see Leuven *et al*. 2004).

4.   Results

4.1.   Heterogeneity in the Return to Adult Literacy

The estimation sample includes Chilean male employees between the ages of 18 and 65. The dependent variable in the earnings regressions is the logarithm of the hourly wage, calculated using information on yearly earnings from wages, hours worked per week and weeks worked per year.

The mean values of the logarithm of hourly wage, years of schooling, achievement score and years of potential experience, as well as the mean values of years of schooling, achievement score and years of experience by earnings quantile, are reported in Table A1 of the Appendix. As expected, years of schooling and achievement scores increase by earnings quantile, while higher paid employees have less average years of experience (a younger lot).

In the estimation of earnings functions, achievement scores (IALS score) have been standardized. Therefore, the estimated coefficient of IALS score measures the approximate percentage change in the hourly wage arising from a one standard deviation increase in the score. Likewise, the coefficient of the score-years of schooling interaction term measures the approximate percentage change in the hourly wage arising from a one standard deviation increase in the score, interacted with one additional year of schooling.

Inclusion of the direct measure of literacy skill in the standard Mincerian earnings function reduces the return to schooling by about 27 percent (see appendix Table A2 which presents the OLS regression results for equation (6)), while a one standard deviation increase in the score increases earnings by nearly 20 percent. This is approximately equivalent to the effect on earnings of two additional years of schooling. Once both the achievement score and its interaction with years of schooling are included (column 4), the interaction term is positive and significant on average. While the implied return to cognitive skill (at between 0.16 and 0.19)[5] is of comparable magnitude to that in column 3, here most of the effect is through the interaction of skill with education (evaluated at mean years of schooling). From column 5, after including father's

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[5] Estimated as the partial derivative, evaluated at mean years of schooling.

education, having a father with at least secondary education is associated with an increase in earnings by about 25 percent; otherwise the results are similar to those in column 4.[6]

Quantile regression results are more illuminating. The standard Mincerian equations estimated by earnings quantile (which are useful for purposes of comparison with other quantile regression estimates for Chile, as well as with the achievement-augmented quantile regression estimates), show that without controlling for the IALS score, quantile wage premiums associated with one additional year of schooling exhibit a U-shaped pattern (Table A4). At the low end of the distribution, estimates are less precise compared to higher-up in the wage distribution. The 90th-10th inter-quantile difference is about 2 percentage points (not significant at the 10% level), while the 90th-25th inter-quantile difference is about 4.5 percentage points (significant at the 5% level). These estimates are qualitatively similar to those obtained by Patrinos *et al.* (2009) and Montenegro (2001), which suggest that those with higher (unobserved) skills benefit more from additional investments in schooling.

Controlling only for literacy skill (Table A3) we obtain an estimate of the effect of skill on earnings (both direct and indirect, though its interaction with schooling). This effect varies little across quantiles; the 90th-10th inter-quantile difference is not significant at the 10% level. One standard deviation increase in the score increases earnings by between one-quarter and one-third. At lower quantiles, skill alone explains about the same amount of the variance in earnings as in the standard Mincerian specification.

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[6] We also attempted to control for the interaction of skill with experience, as it is possible that basic skills could improve with learning on the job. The coefficient was small and statistically insignificant; furthermore, inclusion of this interaction term introduces a multicollinearity problem, over and above what is usually present due to the experience and squared experience controls.

The results after controlling for the independent effect of skill, along with schooling, experience and its square[7], are presented in Table 1. Schooling returns by quantile now exhibit a sharp and strictly increasing pattern, with a 90th-10th inter-quantile difference of nearly 7 percentage points (significant at the 5% level). The independent effect of skill is positive and highly significant up to the 75th percentile of earnings, suggesting that a one standard deviation increase in the score increases earnings by about 20 percent at lower quantiles and a little less than that at the median. However, this effect declines beyond the median and disappears at the 90th percentile. Comparing the effect of an increase in the score to the effect of one additional year of schooling, the effect of one standard deviation increase in the score is equivalent to 3.5, 4, 2, and 1.5 additional years of schooling for quantiles 10, 25, 50 and 75 respectively. The independent effect of father's education is strong,[8] especially around the median; having a father with at least secondary education is associated with 17-35 percent higher earnings, comparable to between 2 and 6 additional years of schooling. Estimates of the wage effect of schooling when skill is not controlled for are, therefore, upward biased except for the 90th percentile. However, one has to note here that, the skills captured by the IALS survey are basic skills (functional literacy); such skills are particularly relevant for workers at lower points of the earnings distribution and possibly around the median. For workers at higher points in the distribution, higher level skills (likely not captured by the IALS score) are expected to influence earnings. Hence, at the top of the distribution,

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[7] Given the absence of a variable on actual experience, what is used is potential experience (age-years of schooling-6).

[8] Using the same mother education dummy, resulted in an insignificant coefficient in the presence of the father education dummy; furthermore, the sample size decreases further, since there is a small number of missing values in the father and mother education variables.

the coefficient of years of schooling along with the signaling value of schooling partly reflects the effect of such higher skills.

Table 1: Log Hourly Wage– Quantile Regressions (Male employees)

Dependent Variable: log of hourly wage	Q10	Q25	Q50	Q75	Q90
Years of schooling	0.056	0.056	0.080	0.092	0.123
	(3.00)	(4.60)	(6.64)	(8.13)	(5.18)
Experience	0.027	0.035	0.020	0.0006	0.008
	(2.18)	(4.52)	(2.61)	(0.07)	(0.51)
Exp. Squared	-0.0004	-0.0005	-0.0002	0.0001	0.0002
	(1.53)	(2.92)	(1.00)	(1.21)	(0.57)
Stand. Score	0.196	0.225	0.161	0.130	-0.021
	(2.62)	(4.67)	(3.35)	(2.89)	(0.22)
Father at least secondary school	0.168	0.347	0.318	0.288	0.246
	(1.34)	(4.30)	(3.97)	(3.82)	(1.56)
Constant	4.80	5.03	5.30	5.72	5.78
	(19.5)	(31.7)	(33.5)	(38.5)	(18.5)
PseudoR^2	0.097	0.125	0.161	0.187	0.185
N	726	726	726	726	726

Note: Sampling weights included. t-values in parentheses

After controlling for both the independent effect of skill and its interaction with years of schooling (Table 2), at the lowest (10th) quantile of earnings, the independent effect of literacy skills is very strong, suggesting that one standard deviation increase in the score increases earnings by about 35 percent. The small negative (but insignificant) effect of the interaction term at the lower end of the distribution suggests that quantity of schooling and basic skills are substitutes. At higher points in the distribution the picture is drastically different. The independent effect of skill is insignificant at the 25th to 75th percentiles (and negative and significant at the 90th). Instead, what becomes progressively more important as one goes to higher points in the distribution is the earnings-enhancing, complementary relationship between skill and quantity of schooling. Estimates of the implied return to skill (estimated using estimates of mean years of schooling at specific quantiles), range from 0.15 to 0.35 and are higher at the two ends of

the earnings distribution. After controlling for the independent effect of father's education, the return to an additional year of schooling tends to increase at higher points of the distribution; however, the 10th-90th inter-quantile difference for the coefficient of years of schooling (at 0.053) is not significant at the 10% level, while the corresponding 25th-90th difference (at 0.047) is significant at the 10% level.

Table 2: Log Hourly Wage– Quantile Regressions (male employees)

Dependent Variable: log of hourly wage	Q10	Q25	Q50	Q75	Q90
Years of schooling	0.054	0.060	0.071	0.085	0.107
	(1.98)	(4.87)	(5.95)	(6.53)	(4.63)
Experience	0.030	0.037	0.027	0.016	0.009
	(1.63)	(4.56)	(3.39)	(1.85)	(0.57)
Exp. Squared	-0.0004	-0.0005	-0.0003	-0.0001	0.0002
	(1.04)	(2.91)	(1.86)	(0.37)	(0.55)
Standardized Score	0.330	0.066	0.006	-0.053	-0.418
	(1.73)	(0.77)	(0.08)	(0.58)	(2.59)
Stand. Score*years of schooling	-0.013	0.016	0.020	0.016	0.052
	(0.75)	(2.02)	(2.61)	(1.94)	(3.49)
Father at least secondary school	0.217	0.315	0.341	0.288	0.116
	(1.19)	(3.84)	(4.27)	(3.33)	(0.75)
Constant	4.78	4.95	5.27	5.69	5.81
	(13.5)	(31.0)	(34.0)	(33.9)	(19.4)
PseudoR^2	0.100	0.128	0.169	0.192	0.208
N	726	726	726	726	726

Note: Sampling weights included. t-values in parentheses

Summarizing, for less skilled workers, quantity of schooling contributes little to earnings; rather basic skills (quality) are the key to higher earnings. On the other hand, those at the top of the distribution (therefore, more skilled) benefit much more from acquiring (or signaling through) more schooling, and from the interaction of additional schooling with skill.

4.2.   Origin of Skill

Note that when the measure of skill used is the raw score, one cannot account for the origin of skill. For example the IALS score captures a wide range of skills acquired by an

individual, including those acquired outside of school (such as within the family). Therefore our earlier methodology assumes that all skills are acquired (or signaled) via schooling.

In what follows, we explore an alternative methodology in obtaining additional information about the relative magnitudes of the components of the wage effect of schooling by origin of skill. Following Ishikawa and Ryan (2002) (see also Tyler, 2004), we partition the adult skill measure (IALS score) by first regressing it on an array of variables associated with different sources of learning (see Table A5):

$$IALS_i = a_1 Z_{1i} + a_2 Z_{2i} + a_3 Z_{3i} + e_i \qquad (7)$$

where Z_1 is the vector of schooling benchmarks[9], Z_2 a vector of parents' education variables (father's and mother's highest education dummies) along with home investment variables (frequency of reading books, frequency of attending plays, concerts, etc.)[10], while Z_3 is a vector of other controls (in our case, age and urban/rural residence of the individual).

Subsequently, the coefficients of schooling benchmarks are used to generate estimates of two independent variables: one being a measure of skills acquired from schooling (SCS), estimated from: $a_1 Z_{1i}$ and the other (NCSC) a measure of skills acquired elsewhere, estimated as: $IALS_i - a_1 Z_{1i}$. Following estimation, skills associated with schooling (SCS) account for about 25 percent of all basic skills on average. The

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[9] An alternative would be to regress the score on both years of schooling (as a measure of quantity) and education level (as a measure of quality); this, however, introduces severe multicolinearity, a problem which is avoided with the approach taken. Table A6 in the appendix gives the variance inflation factors for the regressions in Table 3 following estimation of SCS and NSCS using equation (7).

[10] From the questions in the section on "General activities", frequency of reading books exhibits the highest association with the IALS score.

estimated proportion of these skills increases with education level (from 12 percent at the primary to 39 percent at the university level).

It should, however, be acknowledged that in the above described procedure and in the absence of a proper instrument (such as level of skill at an early age), a measurement error bias is likely to arise. There are two possible sources of such a bias. First, the schooling variable (years of schooling) is subject to measurement error as well as unmeasured variation in school quality (Ishikawa and Ryan 2002). Second, literacy scores are estimates subject to error. As a result, when estimating earnings equations using the IALS score or independent variables generated from it, the estimated coefficients are likely to be biased.

Table 3 gives the results from regressions which use separate measures for schooling and non-schooling skills as controls (columns 4 and 5). From column 2, on average one standard deviation increase in the raw score increases earnings by almost 20 percent, while the coefficient of years of schooling is about 8 percent per additional year. In column 3, when only skills associated with schooling are controlled for, the coefficient of years of schooling increases substantially as it captures a mixture of the signaling value of schooling and skills not related to schooling, while the coefficient of skills associated with schooling is small and not statistically significant. In columns 4 and 5, the separate estimates of the effect of skills by origin suggest that non-schooling skills are rewarded more than school-related skills (one standard deviation increase in such skills is associated with a 12-14 percent increase in earnings), while the signaling value of schooling is substantial, at about 10%. After controlling for father's education (in the presence of father's education, the effect of mother's education is small and statistically

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insignificant, hence omitted), having a father with at least secondary certificate is associated with about 30 percent increase in earnings on average.

Table 3: Log Hourly Wage– OLS Regressions (Male employees)

	(1)	(2)	(3)	(4)	(5)
Years of Schooling	0.110	0.080	0.117	0.096	0.109
	(10.35)	(6.00)	(3.82)	(2.96)	(2.99)
Experience	0.013	0.015	0.012	0.014	0.015
	(1.62)	(1.89)	(1.52)	(1.72)	(1.70)
Experience squared	0.0000	-0.0000	0.0000	0.0000	-0.0000
	(0.20)	(0.12)	(0.23)	(0.03)	(0.18)
Standardized Score	-	0.185	-	-	-
		(4.22)			
Standardized SCS	-	-	0.035	0.028	-0.040
			(0.28)	(0.21)	(0.28)
Standardized NSCS	-	-	-	0.132	0.110
				(4.45)	(3.22)
Father at least secondary school	-	-	-	-	0.292
					(2.90)
Constant	5.16	5.41	5.10	5.27	5.00
	(33.2)	(32.1)	(17.9)	(17.6)	(14.5)
Adj. R^2	0.186	0.205	0.186	0.206	0.245
N	893	893	893	893	726

Note: Sampling weights included in regression with robust standard errors; t-values in parentheses.

Table 4 gives quantile regression estimates of the effect of skill at various points of the earnings distribution using the specification of column 5 in Table 3. The results indicate that, of the type of skills captured in the IALS survey, those not associated with schooling are important, except for workers at the top of the earnings distribution; for such workers, the reward for more education (through its signaling value) is high, while the reword for both schooling and non-schooling basic skills is insignificant.

Table 4: Log Hourly Wage– Quantile Regressions (Male employees)

	Q10	Q25	Q50	Q75	Q90
Years of schooling	0.106	0.099	0.095	0.122	0.134
	(2.80)	(3.84)	(3.88)	(5.43)	(2.56)
Experience	0.033	0.030	0.015	0.004	0.009
	(2.65)	(3.57)	(1.90)	(0.59)	(0.50)
Exp. Squared	-0.0004	-0.0004	-0.0000	0.0002	0.0002
	(1.98)	(2.23)	(0.26)	(1.47)	(1.52)
Stand. SCS	-0.083	-0.068	0.028	-0.091	-0.052
	(0.49)	(0.59)	(0.26)	(0.91)	(0.22)
Stand. NSCS	0.136	0.174	0.111	0.071	0.009
	(2.58)	(4.86)	(3.27)	(2.27)	(0.13)
Father at least secondary	0.198	0.356	0.321	0.321	0.225
school	(1.57)	(4.15)	(3.94)	(4.29)	(1.30)
Constant	4.26	4.69	5.19	5.45	5.67
	(11.5)	(18.6)	(21.6)	(24.8)	(11.1)
PseudoR^2	0.099	0.127	0.162	0.188	0.185
N	726	726	726	726	726

Note: Sampling weights included; t-values in parentheses.

In this paper, besides innate ability, non-cognitive skills are also not observed and therefore not controlled for; however, cognitive skills are not the only skills that are relevant, and this has been frequently stressed in the literature (see, for example, Heckman *et al*. 2006; Cunha and Heckman 2008; Green and Riddell 2002; Bowles and Gintis 2000; Bowles *et al*. 2001). One can, for example, observe that the amount of additional variation in earnings that is typically explained (including this study) by the inclusion of the cognitive measure available is rather modest. Furthermore, the inclusion of other explanatory variables, such as experience, parental background and other individual characteristics, typically explains less than half of the variation in earnings. Non-cognitive skills may be productive on their own right, and the effect may be large. Non-cognitive traits include attitude, communication skills, motivation, persistence, as well as dependability and even docility (especially in low skill labor markets). Bowles

and Gintis (2000) argue that non-cognitive skills may account for more than half of measured returns to schooling, and that most of the schooling impact is through endowing individuals with such non-cognitive traits.

Heckman *et al*. (2006) agree, and further suggest that latent non-cognitive skills, corrected for schooling and family background raise wages through their direct effects on productivity and through their indirect effects on schooling and work experience. Cunha and Heckman (2008) support the view that non-cognitive skills promote the formation of cognitive skills but not vice versa; parental investments are more effective in raising non-cognitive skills and have different effects at different stages of the child's life cycle with cognitive skills affected more at early ages and non-cognitive skills affected more at later ages.

5.   Conclusion

This paper, using data from Chile finds that the inclusion of the adult literacy score, after conditioning for years of schooling and experience, reduces the return to schooling by about 27 percent on average. Furthermore, it is shown that a one standard deviation increase in the score increases earnings by 15-20 percent. Quantile regression results, however, exhibit considerable heterogeneity. At the lower part of the earnings distribution (and to a large extent in the middle of the distribution), workplace-related literacy is very important in determining earnings. At higher points in the distribution, however, the reward of an additional year of schooling reflects its signaling value. Without distinguishing for origin of skill, the contribution of literacy skills are mostly through their interaction with schooling, especially at higher points of the earnings distribution.

When skill is partitioned by origin, those skills not associated with schooling were more important in determining earnings in Chile (1998), except for workers at the top end of the earnings distribution; for such workers (at the top end of the distribution), the signaling value of schooling is high, while the reward for both schooling and non-schooling basic cognitive skills is insignificant.

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Appendix

Table A1: Means of Variables by Earnings Quantile, Male Employees

Variable	Overall mean	10th	25th	50th	75th	90th	99th
Log of hourly wage	6.41	5.56	5.95	6.17	6.87	7.46	8.84
	(0.88)	(0.63)	(0.12)	(0.13)	(0.16)	(0.16)	(0.36)
Years of schooling	9.3	6.9	7.3	8.4	9.6	11.5	13.4
	(4.3)	(3.9)	(3.9)	(3.7)	(3.8)	(3.6)	(4.4)
IALS score	209.3	167.3	181.5	198.8	221.1	237.3	259.3
	(62.8)	(65.1)	(61.4)	(54.5)	(55.7)	(51.7)	(54.7)
Years of experience	21.5	25.7	22.9	21.9	20.4	20.2	17.9
	(13.4)	(14.5)	(14.8)	(13.5)	(11.9)	(12.7)	(12.5)
N	892*	88	159	217	211	125	82

Note: Sampling weights included standard deviation in parentheses.
*Includes ten observations for those with earnings which exceed the 99th percentile.

Table A2: Returns to Schooling (Male employees)

Dependent Variable: log of hourly wage	(1)	(2)	(3)	(4)	(5)
Years of schooling	-	0.110	0.080	0.074	0.079
		(10.35)	(6.00)	(5.33)	(4.44)
Experience	-	0.013	0.015	0.019	0.020
		(1.62)	(1.90)	(2.25)	(2.11)
Exp. Squared	-	-0.0000	-0.0000	-0.0001	-0.0002
		(0.20)	(0.12)	(0.80)	(0.80)
Standardized Score	0.356	-	0.185	0.017	0.017
	(10.0)		(4.22)	(0.23)	(0.19)
Standardized Score*years of schooling	-	-	-	0.019	0.015
				(2.32)	(1.72)
Father at least secondary completed	-	-	-	-	0.254
					(2.52)
Constant	6.46	5.16	5.41	5.39	5.27
	(196.7)	(33.2)	(32.1)	(31.6)	(26.5)
R^2		0.145	0.186	0.205	0.212	0.236
N		893	893	893	893	726

Note: Sampling weights included in regression with robust standard errors; t-values in parentheses.

Table A3: Returns to Skill Using Quantile Regression (Male employees)

Dependent Variable: log of hourly wage	Q10	Q25	Q50	Q75	Q90
Standardized Score	0.284	0.264	0.351	0.374	0.341
	(6.60)	(8.13)	(13.2)	(10.1)	(6.62)
Constant	5.67	6.04	6.45	6.86	7.34
	(141.2)	(199.2)	(259.7)	(198.3)	(152.7)
PseudoR^2	0.061	0.067	0.099	0.093	0.108
N	893	893	893	893	893

Note: Sampling weights included; t-values in parentheses.

Table A4: Returns to Schooling Using Quantile Regression – Standard Earnings Functions (Male employees)

Dependent Variable: log of hourly wage	Q10	Q25	Q50	Q75	Q90
Years of schooling	0.103	0.075	0.112	0.112	0.121
	(7.02)	(9.30)	(13.9)	(13.1)	(7.34)
Experience	0.027	0.019	0.028	-0.002	0.003
	(2.16)	(2.74)	(4.06)	(0.33)	(0.24)
Exp. Squared	-0.0003	-0.0002	-0.0002	0.0004	0.0003
	(1.43)	(1.41)	(1.80)	(2.55)	(1.21)
Constant	4.35	5.09	5.01	5.70	5.87
	(18.4)	(39.4)	(38.9)	(41.8)	(22.1)
PseudoR^2	0.061	0.075	0.112	0.151	0.171
N	893	893	893	893	893

Note: Sampling weights included. t-values in parentheses.

Table A5: Determinants of IALS score, OLS regression (Male employees)

Characteristic	Coefficient (t-value)
Primary	19.48
	(2.32)
Lower Secondary	51.18
	(7.49)
Upper Secondary	77.37
	(11.1)
Higher Non-University	95.66
	(11.0)
University/Post graduate	111.0
	(14.4)
Age	-0.050
	(0.30)
Urban	8.50
	(1.90)
Father >= Upper Secondary	8.48
	(1.59)
Mother >= Upper Secondary	10.33
	(1.63)
Reads books at home frequently	27.05
	(4.26)
Attends plays, concerts, etc., frequently	6.03
	(1.37)
Constant	126.6
	(13.6)
Adj. R^2	0.558
N	753

Note: Sampling weights included in regression with robust standard errors; t-values in parentheses..

Table A6: Variance inflator factors (VIF) (Equations in Table 3)

	(1)	(2)	(3)	(4)
Years of schooling	1.58	2.66	11.21	11.71
Experience	11.94	11.99	11.81	12.25
Experience^2	11.64	11.71	10.21	11.86
Standardized Score	-	2.05	-	-
Standardized SCS	-	-	11.15	11.39
Standardized NSCS	-	-	-	1.07
Mean VIF	8.39	7.10	11.60	9.66