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Cognitive Ability, Heterogeneity, Endogeneity and Returns to Schooling in Chile: Outcomes of the 1981 Capitation Grant Scheme

Harry Anthony Patrinos*
World Bank, Washington D.C.

Chris Sakellariou
Department of Economics, Humanities and Social Sciences
Nanyang Technological University, Singapore

Abstract: The objective of this paper is to exploit the unique information on cognitive ability contained in the International Adult Literacy Survey (IALS) data, for an in depth examination of the importance of cognitive skills for heterogeneous individuals using: (a) a quantile regression methodology which allows for an interaction between schooling and cognitive skills and (b) Instrumental Variables estimation to evaluate the relationship between quantity and quality of schooling outcomes following the 1981 "vouchers" reform in Chile. On average, inclusion of the direct measure of cognitive ability reduces the return to schooling by about 25 percent – roughly equivalent to two additional years of schooling, while a one standard deviation increase in the score increases earnings by 15-20 percent. However, for those in the lowest earnings/ability quantile, education qualifications at any education level do not contribute to earnings; rather cognitive ability is the key to higher earnings. On the other hand, those in high quantiles (higher unobserved ability) benefit much more from acquiring more schooling, and from the interaction of schooling and cognitive ability. Using a binary instrument based on the 1981 reform, we find that the main beneficiaries of the reform were those who at the time were entering primary school or who were existing pupils in basic education. For this treated group of pupils, only a small part of the estimated return to schooling is due to classical ability bias. However, once the treated group is expanded to include secondary school students, the pure return to schooling decreases dramatically while the return to cognitive skills is very large, suggesting that most of the estimated return from a Mincerian earnings function is due to classical ability bias.

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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 estimation by ordinary least Squares (OLS) will yield biased estimates of the return to schooling.

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 with low ability may not benefit as much from investing in education, compared to individuals in the upper part of the ability distribution; for the latter, ability 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 (1997) 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 for exogenous variation in educational attainment, such as institutional changes in the schooling system in the form of changes in compulsory schooling laws, abolition if 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 1993; Card 1995; Harmon and Walker 1995; Meghir and Palme 2005; for developing countries, see DuFlo 1998; Patrinos and Sakellariou 2005; Sakellariou 2006). 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. We use this approach in the second part of the paper.

The third approach, and also the approach used in the first part of this paper, uses achievement test scores measuring cognitive ability, and employ them as additional controls in the earnings function. One should, however, keep in mind that both schooling and the test score 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 2005). We use the International Adult Literacy Survey (IALS) data, which contain direct measures of cognitive ability. 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 exists in Montenegro (2001), who found strong increasing returns by quantile over many years, as well as in the multi-country study by Patrinos *et al*. (2006), who reported similar results. Both studies (without controlling for any measure of ability) looked at the pattern of returns by quantile. The concept of ability utilized in the above two, as well as other studies (for example Arias et. al., 2001), relates to those unobservable, earnings-enhancing, human capital characteristics of an individual, rather that 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, the only country in the survey outside Europe and North America. Blau and Khan (2001) examined the role of cognitive skills 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. They find that cognitive achievement is an important determinant of earnings in all countries examined except Poland and Finland. They also find that about one-third of the variation in relative wages between skill groups across countries is explained by differences in net supply of skill groups. Green and Riddell (2002) used the measure of literacy in the IALS dataset to examine the influence of cognitive and unobserved skills on earnings in Canada. They find that cognitive skills contribute significantly to earnings and that their inclusion in earnings equations reduces the measured impact of schooling. They also find that the impact of literacy on earnings does not vary across quantiles of the earnings distribution; schooling and literacy do not interact in influencing earnings. Their findings suggest that cognitive and unobserved skills are both productive but that having more of one skill does not enhance the other's productivity. Devroye and Freeman (2001) used the IALS survey and found that skill inequality among advanced countries explains only about 7 percent of the cross-country differences in earnings inequality. They also find that the bulk of cross country differences in earnings inequality occur within skill groups, not between them. Hanushek and Zhang (2006) use IALS data to control for the quality of education's impact on the returns to education. They construct quality-adjusted measures of schooling attained at different time periods and use these along with international literacy test information to estimate returns to skills for 13 countries. Their estimated returns to quality-adjusted education are considerably higher than the traditional estimate for most countries, but these are offset to varying degrees by selection biases on ability. The combined corrections alter significantly the pattern of returns to schooling estimated from Mincer wage equations.

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 ability levels. Intuitively, an estimate of the average return to schooling probably over-estimates the return for low ability individuals and under-estimates the return to high ability individuals. One should, therefore allow ability to affect the rate of return to schooling investments.

We incorporate the literacy score as a measure of cognitive ability to proxy for unobserved effects. We expect that the inclusion of a direct measure of cognitive ability will reduce the estimated education coefficient, so that the coefficient on education then captures the effect of education alone having controlled for cognitive skills.

The effect of introducing ability differences is two-pronged. First, the more able individuals may be able to 'convert' schooling into human capital more efficiently than the less able, and this raises the return to schooling for the more able. In this case, one can conclude that ability and education are complementing each other in producing human capital. On the other hand, the more able may have higher opportunity costs since they may have been able to earn more in the labor market, if ability to progress in school is positively correlated with the ability to earn, and this reduces the rate of return to schooling (Harmon and Walker 2000). Given a distribution of wages, we assume that this distribution reflects the distribution of inherent unobserved ability. As a result, lower ability individuals predominate in the lower quantiles of the distribution and higher ability individuals predominate in the upper quantiles of the distribution.

The model in which both the measure of ability and its interaction with schooling affect earnings and the ability specific return to schooling is outlined below (Griliches 1977; Nordin 2005):

$$\text{Ln } w_i = a + \text{ß}S_i + ?A_i + e_i \qquad (1),$$

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

$$\text{Ln } w_i = a + \text{ß}(f(A_i))S_i + ?A_i + e_i \qquad (2).$$

Using the test score as a proxy for cognitive ability:

$$\text{Ln } w_i = a + \text{ß}(f(T_i))S_i + ?T_i + e_i \qquad (3),$$

where T is the IALS test score which is assumed to perfectly measure cognitive ability. Assuming a linear relationship between test score and cognitive ability:

$$f(T_i) = t_0 + t_1T_i \qquad (4),$$

we obtain the following earnings equation:

$$\text{Ln } w_i = a + t_0S_i + t_1T_iS_i + ?T_i + e_i \qquad (5).$$

Finally, including experience, its square and other covariates:

$$\text{Ln } w_i = a + t_0S_i + t_1T_iS_i + ?T_i + \exp + \exp^2 + X_i + e_i \qquad (6),$$

where X is a vector of other covariates.

Equation (6) is estimated using both Ordinary Least Squares (OLS) to obtain estimates of average return to schooling, as well as quantile regressions. When it is suspected that various exogenous variables (such as schooling, cognitive ability and experience) influence parameters of the conditional distribution of the dependent variable other than the mean, quantile regressions are particularly useful, because they allow the full characterization of the conditional distribution of the dependent variable, rather than the conditional mean only. The quantile regressions methodology, therefore, 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. The quantile regression model is outlined in Koenker and Bassett (1978) and Buchinsky (1997).

OLS and quantile regressions will also be used to estimate the corresponding equations in which different levels of education replace the years of schooling variable, to gain an insight as to how the pattern of returns varies with education level.

Data

The International Adult Literacy Survey (IALS) was carried out in 20 countries[1] between 1994 and 1998, a project undertaken by the governments of the countries and three intergovernmental organizations[2]. 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 IALS 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

[1] 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 UK and the US.
[2] OECD, European Union and UNESCO.

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 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, 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 dataset, 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).

Results

The working sample includes males employed for wages 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, cognitive achievement score and years of experience, as well as the mean values of years of schooling, cognitive achievement score and years of experience by earnings quantile, are reported in Table A1 of the Appendix. As expected, years of schooling and cognitive 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, cognitive achievement scores have been standardized. Therefore, the estimated coefficient of cognitive achievement measures the approximate percentage change in the hourly wage arising from a one standard deviation increase in the score. Likewise, the coefficient of cognitive achievement-years of schooling interaction variable measures the approximate percentage change in the hourly wage arising from a one standard deviation increase in cognitive achievement, interacted with one additional year of schooling.

Inclusion of the direct measure of cognitive ability in the traditional earnings function reduces the return to schooling by about 25 percent (see Table A2 which presents the OLS regression results for equation (6)), while a one standard deviation increase in cognitive achievement increases earnings by a significant 15 percent. This is approximately equivalent to the effect on earnings of two additional years of schooling. Once both the cognitive achievement and its interaction with years of schooling are included (column 4), the interaction term is positive and significant on average, while the effect of cognitive achievement becomes insignificant.

Quantile regression results are more illuminating (see Tables 1, A3, A4). The traditional Mincerian equations by earnings quantile, which are useful for purposes of comparison with other quantile regression estimates for Chile, as well as with the cognitive achievement-augmented quantile regression estimates, show that without controlling for cognitive achievement, quantile returns to one additional year of schooling exhibit a U-shaped pattern, increasing after the 10^{th} quantile. The 90^{th}-10^{th} inter-quantile difference is about 2 percentage points, while the 90^{th}-25^{th} inter-quantile difference is about 4.5 percentage points. These estimates are qualitatively similar to those obtained by Patrinos *et al*. (2006) and Montenegro (2001), which suggest that those with more (unobserved) ability, are able to benefit more from additional investments in schooling.

Once the estimates incorporate measures of cognitive skills (both direct and through schooling), then there is little variation across quantiles (Table A3 in the appendix). A one standard deviation increase in cognitive achievement increases earnings by between one-quarter and one-third. In lower quantiles (10^{th} and 25^{th}), cognitive achievement alone explains about the same amount of the variance in earnings as the specification in the standard Mincerian specification.

The results after controlling for the independent effect of cognitive achievement, along with schooling, experience and its square, are presented in Table 1. Schooling returns by quantile now exhibit a sharp and strictly increasing pattern, with a 90^{th}-10^{th} inter-quantile difference of 7.5 percentage points. The independent effect of cognitive achievement is positive and highly significant up to the 75^{th} quantile of earnings, suggesting that a one standard deviation increase in achievement increases earnings by about 20 percent. However, this effect all but disappears at the 90^{th} quantile. Comparing the effect of an increase in achievement scores to the effect of one additional year of schooling, the effect of one standard deviation increase in the score is equivalent to the effect of 5, 3.5, 3, and 2 additional years of schooling for quantiles 10, 25, 50 and 75. Schooling return estimates when cognitive achievement is not controlled for are, therefore, upward biased except for the 90^{th} quantile of earnings, where the estimate remains approximately unchanged after controlling for cognitive achievement.

Table 1: Returns to Schooling and Cognitive Achievement – Quantile Regressions
(Male employees)

Dependent Variable: log of hourly wage	Q10	Q25	Q50	Q75	Q90
Years of schooling	0.043	0.057	0.069	0.087	0.118
	(3.0)	(5.5)	(4.8)	(6.8)	(4.6)
Experience	0.026	0.026	0.022	0.001	0.003
	(2.6)	(3.4)	(2.2)	(0.1)	(0.3)
Exp. Squared	-0.0003	-0.0003	-0.0002	0.0003	0.0003
	(1.7)	(1.8)	(1.1)	(1.8)	(1.2)
Stand. $Score_{IALS}$	0.205	0.197	0.214	0.174	0.020
	(4.0)	(4.9)	(4.0)	(4.0)	(0.3)
Constant	4.98	5.17	5.49	5.83	5.88
	(26.9)	(35.9)	(27.3)	(33.9)	(17.7)
PseudoR^2	0.082	0.099	0.139	0.178	0.213

Note: t-values in parentheses

Controlling for both the independent effect of the cognitive ability measure and its interaction with years of schooling, it is shown that at the lowest quantile the independent effect of cognitive achievement is very strong, indicating that a one standard deviation increase in the score increases earnings by about one-third, while the interaction term is negative (see Table 2). For the higher quantiles the picture is drastically different. The independent effect of cognitive achievement is insignificant in quantiles 25 to 75 and negative at the 90th quantile. Instead, what matters is the earnings-enhancing, complementary relationship between cognitive achievement and schooling. A one standard deviation increase in the score combined with one additional year of schooling increases earnings by between 1.5 percent (25th quantile) and 4.5 percent (90th quantile), while the return to schooling estimate at the highest (90th) quantile is now about 15 percent lower compared to the one reported in Table 1 (the specification without the interaction term).

Table 2: Returns to Schooling and Cognitive Achievement – Quantile Regressions (male employees)

Dependent Variable: log of hourly wage	Q10	Q25	Q50	Q75	Q90
Years of schooling	0.060	0.055	0.065	0.082	0.100
	(3.7)	(5.5)	(4.5)	(5.7)	(5.1)
Experience	0.022	0.034	0.030	0.002	0.014
	(2.0)	(4.6)	(2.9)	(0.2)	(1.3)
Exp. Squared	-0.0002	-0.0005	-0.0004	0.0002	-0.0000
	(1.2)	(3.2)	(2.0)	(1.1)	(0.1)
Standardized $Score_{IALS}$	0.370	0.065	-0.030	-0.119	-0.309
	(4.1)	(1.0)	(0.3)	(1.5)	(2.8)
Stand. $Score_{IALS}$*years of schooling	-0.022	0.015	0.026	0.026	0.045
	(2.5)	(2.5)	(3.0)	(3.5)	(5.3)
Constant	4.89	5.11	5.40	5.87	5.87
	(24.4)	(38.3)	(27.3)	(30.1)	(20.3)
PseudoR^2	0.086	0.102	0.149	0.193	0.247

Note: t-values in parentheses

Summarizing, for individuals in the lowest earnings quantile, education qualifications at any level (quantity of schooling) do not contribute to earnings; rather cognitive achievement (quality) is the key to higher earnings. On the other hand, those in high quantiles (therefore, those of higher ability) benefit much more from acquiring more schooling, and from the interaction of additional schooling with ability.

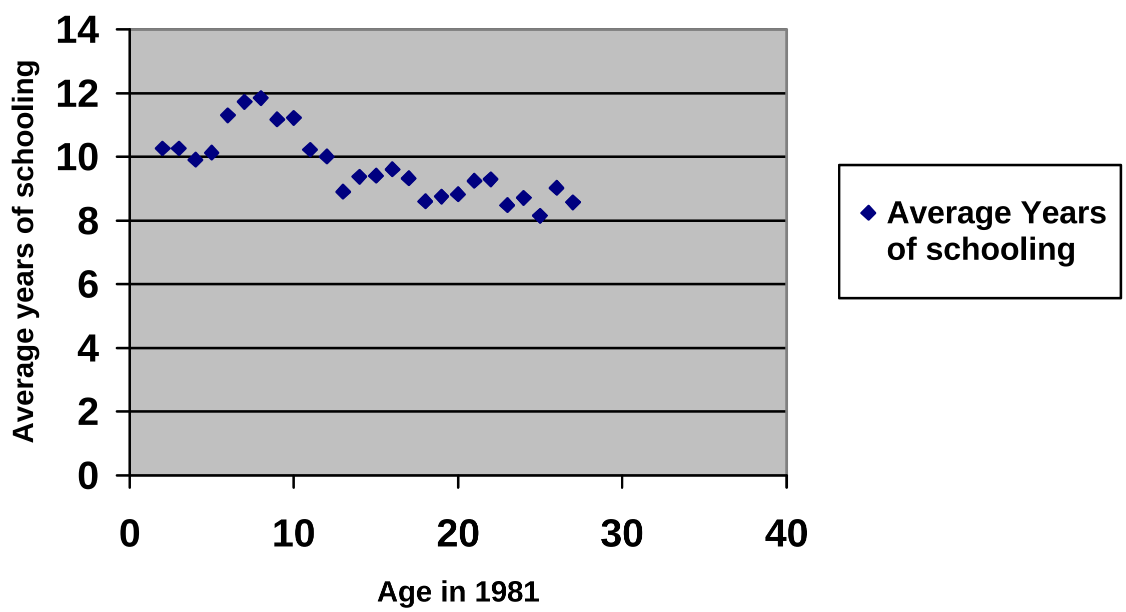
Cognitive skills are, therefore, important in determining earnings. However, cognitive skills are not the only skills that are relevant, and this has been frequently stressed in the literature (see, for example, Heckman *et al*. 2006; Green 2001; Bowles and Gintis 2000; Bowles *et al*. 2001). One can, for example, observe that the amount of additional variation in earnings that is typically explained (including this study) by the inclusion of the cognitive achievement measure is rather modest. Furthermore, the inclusion of other explanatory variables, along with education and the measure of cognitive achievement, such as experience, parental background and other individual characteristics, typically explains less than half of the variation in earnings. Non-cognitive ability may be productive on its 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.

An Evaluation of the 1981 Capitation Grant (Vouchers) Scheme

In this part of the paper we use the school reform of 1981 to identify a binary instrument and estimate returns to schooling from IV, with and without controlling for cognitive skills. Chile, among developing countries, was a pioneer and has gone farther than any other country to redefine the roles of the state and private sector in education, by separating the financing from the provision of education. Consequently, the dropout rate declined sharply (from 8 percent in 1981 to 2.7 percent in 1982 for basic education and from 8.3 percent to 6.2 percent for secondary education). As a result of the capitation grants paid to schools and the opening of the education system to the private sector, Chile was able to absorb the pressure of secondary school expansion. There was a large shift of students to the private subsidized schools (mainly in major urban areas), whose enrollment increased by 93 percent between 1980 and 1985, at the expense of municipal schools. Despite a decline in public spending for education (from 4 percentage of GDP in 1981 to 2.6 percent in 1990), student intake increased by 42 percent in higher education and by about 15 percentage points in secondary education (Delannoy 2000). As a result, the average years of schooling peak for the cohorts around and immediately after the reform (see Chart 1). Overall, the reform improved the efficiency of the education system (number of students educated per unit of public spending increased significantly over the 1980s, without a significant change in average quality). However, this was achieved at the expense of equity, as subsidized private schools serving a better-informed, better-off population benefited from the opportunities offered by the capitation grants system at the expense of municipal schools which served the less well-off section of the population.

The Chilean voucher system has been studied extensively. Some find that the voucher system had positive impacts on test scores and pre-college examinations (Gallegos 2004, 2002; Contreras and Macias 2002; Sapelli and Vial 2002; Sapelli 2003; Gallegos 2004). Yet others found that there was no impact on test scores, repetition rates or secondary school enrollment rates (Carnoy and McEwan 2000; Hsieh and Urquiola 2003). In addition, Gauri (1998) found that school choice had led to increased social and academic stratification. Bellei (2005) outlines three principal reasons why it is difficult to make comparisons between public and private schools in Chile and how they explain the widely diverging results in individual analyses, all stemming from the lack of random assignment of students to schools: (i) private schools tend to be located in urban areas and serve middle to middle-high income students, (ii) there are wide differences in the level of resources available to schools, even among the same types of schools, and (iii) there is very little information about how families select schools and how private schools select students. Thus, it is difficult to measure the supply of private schools, control for school resources, and the estimates are riddled with selection bias. The studies also differ in the ways that they use control variables such as parental education, school socio-economic status, student characteristics, test-score variation, and so on. Gallegos (2006) explains that the differences in results can be attributed to changes in the voucher and education systems in the mid 1990s. Hoxby (2003) reiterates that existing studies lead to inconclusive evidence of impact due to a lack of random assignment, thus making it difficult to determine whether variation in school choice is endogenous, and lack of pre-treatment data. This paper does not attempt to look at the impact of the reform in this light, but rather use the reform itself as an instrument to estimate the causal effect of education on earnings of the group affected by the 1981 education reform, as well as the effect of the reform on quality of learning.

Chart 1: Average years of schooling by cohort (Age in 1981)



The group affected by the education reform, while consisting of students with a variety of backgrounds, is expected to contain a large proportion of students from a higher socio-economic background and from urban areas. This is because, firstly, in rural areas in Chile, low population density does not permit a choice of schools; and secondly, there is evidence that private-subsidized schools tend to select students to a larger extent than municipal schools (Delannoy 2000), therefore, better private-subsidized schools (as well as some elite municipal schools) facing excess demand practiced screening. According to Gauri (1998), 28 percent of students in the subsidized sector of Santiago had taken tests to be admitted in their current schools.

Furthermore, top-up in fees, lack of transparency in enrollment procedures, and the cost of uniforms constituted de-facto screening devices. As a result, students who attend private-subsidized schools come from higher-income and better educated families compared to municipal schools (but not private non-subsidized schools).

We estimate the returns to schooling for those induced to make schooling decisions (involving quantity or quality) by the change associated with our instrument - the 1981 reform. In this study, the instrument corresponds to a policy of capitation grants which induced a group of individuals to opt for the opportunities that the policy made available. The estimates, therefore, identify a policy relevant return to schooling in Chile, in the sense that one can use the estimates to evaluate this policy.

What is the prior expectation of the magnitude and nature of the results? Instrumental variables estimates of the return to schooling are expected to differ from OLS estimates. While the standard ability bias would suggest that the OLS estimates are biased upwards, empirical evidence from using a variety of, mainly binary, instruments several of which are based on education policy reforms suggest that IV estimates are generally higher that OLS estimates. The dominant explanation for this (as given by Card 2001) is that because of heterogeneity, there is a distribution of returns and OLS and IV estimates correspond to different weighted averages of this distribution; therefore, IV estimates can exceed OLS estimates. Therefore, the fact that the IV estimates are higher than the OLS estimates is interpreted as an indication that the return to the marginal person (the “switchers”) is higher than that of the average person. Furthermore, Carneiro, Heckman and Vytlacil (2005) show that the marginal person can have a return that is substantially lower than the return to the average person, and still the return estimate from IV is greater than the corresponding return from OLS.

In the first part of the paper we found that when cognitive skills are controlled for, the average return assigned to an additional year of schooling decreases by about 25 percent, while one standard deviation increase in the score increases earnings by 15-20 percent. However, from quantile regressions we found that, in the case of Chile, cognitive skills are important mostly to those at the low end of the earnings distribution (that is, those with low cognitive as well as unobserved ability). Furthermore, the dispersion of cognitive scores is highest at the lowest section of the earnings/ability distribution. Assuming that cognitive skills are associated with quality of schooling, and a group of students switched to better quality schools as a result of the reform, we would expect the affected group (especially those who switched to better quality schools at a younger age) to have higher and less dispersed cognitive skills. For example, in Scandinavian countries where we observe high IALS scores and their dispersion is low, the increase in earnings in response to one standard deviation increase in scores is generally low compared to Chile, which has the lowest scores among the IALS group of countries and the dispersion of scores is twice that of Scandinavian countries. Therefore, cognitive skill scores in the IV regressions are expected to be lower compared to the OLS regressions.

The results from OLS regressions for returns to an additional year of schooling and the effects of controlling for the measure of cognitive skills, using a sample of 22-45 years old group of males working for wages, are presented in Table A5. The dependent variable is the logarithm of hourly wage. Inclusion of the direct measure of cognitive ability reduces the return to schooling by about 34 percent, while one standard deviation increase in the score increases earnings by 17 percent. On average, the interaction effect of schooling with cognitive skills is moderately positive and nearly significant.

The results from IV regressions using the instrument based on the capitation grants reform are presented in Table 3. The binary instrument takes the value of 1 for those who at the time of the reform where 6 years or older (22 years or older in 1997 – the year of the survey) and up to 13 years of age included (29 years old in 1997) and 0 otherwise, that is those in the 8 years of basic education. One-third of the observations belong to the group affected by the reform. Two alternative sample specifications were used: 22-65 and 22-45 years of age. Quantitatively, in both cases the estimates were very similar. However, for the 22-45 group the results were more precise; therefore, we present these results. In the first stage, the correlation of years of schooling with the instrument is strong (Shea's partial R^2 is high), indicating that the instrument is sufficiently relevant to explain the endogenous regressor), while the instrument is uncorrelated with the logarithm of hourly wage.

Table 3: Returns to Schooling from IV – Male Employees 22-45 years (Instrument=1 if age in 1981 between 6 and 13 years)

Variable	IV: Reform	IV: Reform	IV: Reform
Years of schooling	0.122	0.102	0.096
	(5.1)	(2.7)	(2.5)
Experience	0.001	0.009	0.015
	(0.5)	(0.5)	(0.8)
Experience squared	0.0002	0.0002	-0.0000
	(0.3)	(0.4)	(0.1)
Standardized IALS score	-	0.086	0.009
		(1.0)	(0.1)
Stand. IALS score-years of schooling interaction	-	-	0.011
			(1.0)
Constant	4.98	5.19	5.19
	(13.3)	(10.2)	(10.5)
Centered R^2	0.144	0.167	0.174
N	586	586	586
First Stage:			
Shea's partial R^2	0.261	0.139	0.130
F-value	205.5	93.6	86.5
[p-value]	[0.000]	[0.000]	[0.000]
Over-identification Test:			
Hansen's J-statistic	Exactly Identified	Exactly Identified	Exactly Identified
Endogeneity Test:			
Durbin-Wu-Hausman statistic	3.95	2.09	1.63
[p-value]	[0.047]	[0.148]	[0.201]

Note: t-values in parentheses

In the standard Mincerian specification, the IV estimate of the return to schooling is about 37 percent higher that the OLS estimate, and the assumption that the schooling variable is exogenous is rejected at the 5 percent level. Here one needs to consider the composition of the group affected by the reform. This group (which in this case consists of pupils in basic education), contains those who switched to private subsidized schools. While there is no conclusive evidence that school choice improved the performance of the median student, it has been argued convincingly that the main effect of unrestricted school choice was an exodus of "middle class" students from public sector schooling (Hsieh and Urquiola 2006) and the practice of screening by private subsidized schools (competing for better students). Furthermore, it is possible that parents tended to select schools which provided good peer groups. Based on this evidence, we attribute the higher IV estimate of the return to schooling to those in a treated group with such characteristics, rather than the average individual.

In column (2), we control for cognitive skills. Without controlling for cognitive ability, cognitive ability will be part of the error term. The assumption of independence implies that the instrument must be independent of cognitive ability. Therefore, when cognitive ability is not controlled for, the instrument is compromised. By controlling for cognitive ability we avoid the problem of using possibly invalid instruments and make our estimates more credible (Carneiro *et. al.* 2005).

When we include the measure of cognitive skills in the equation, the estimate of the return to schooling decreases by about 16 percent (which is much less than the reduction one sees in the OLS regressions), while the contribution of one standard deviation in the cognitive score to earnings is one-half the corresponding estimate from the OLS regressions (8.5 compared to 17 percent). The above results seem to indicate that students who switched to private subsidized schools (in this case those who in 1981 were entering primary school or were already enrolled in basic education), belonged to a rather homogeneous group of students with above average cognitive skills. That is, “better” students formed the bulk of those who switched from public to private subsidized schools. As a result, only a small part of return to schooling estimate is due to classical ability bias. Column (3) indicates that the contribution of cognitive skills is mainly through their interaction with schooling (as was the case in the OLS regressions).

Another instrument (in addition to the policy reform based instrument) is included in the specification presented in Table A6, namely if the pupil's father has at least upper-secondary education. Here the objective is twofold: first, test the over-identifying restrictions and, second, test the hypothesis that if the treated group is an even more privileged one (have taken advantage of the capitation grant system *and* have educated fathers), its cognitive skills will be better and more homogeneous compared to the treated group in Table 3 (which in turn had better and more homogeneous cognitive skills compared to the average individual). Therefore, the contribution of cognitive skills to earnings should be small, while returns to schooling should increase.

Based on the value of Hansen's J-statistic (see Hansen 1982), the null hypothesis (that the instruments are appropriately uncorrelated with the disturbance process) is not rejected (in all cases, that is, columns (1), (2) and (3), p-values are 0.15 or higher). As hypothesized, the contribution of cognitive skills to earnings is nearly zero (column 2), while the schooling-cognitive skills interaction is much less than in Table 2 and statistically insignificant. At the same time, the estimate of the return to schooling increases by between 7-19 percent compared to Table 3.

In Table 3a the binary instrument takes the value of 1 for those who at the time of the reform where 6 years or older (22 years or older in 1997 – the year of the survey) and up to 18 years of age included (34 years old in 1997) and 0 otherwise; that is the group includes all those who could have been affected by the reform, either by switching to private subsidized schools because of their perceived higher quality compared to municipal schools, or by choosing to continue schooling at the secondary level as a result of the increase in the supply of private schools associated with the education reform, which led to a large increase in secondary school participation. Estimates of the return to schooling are now lower by 37 percent in the Mincerian specification and by more than 50 percent when we control for cognitive skills. At the same time, one standard deviation increase in the cognitive score increases earnings by 20 percent, up from 8.5 percent in Table 3. The coefficient estimates are now close to those from OLS, as a result the endogeneity test does not reject the null hypothesis that the difference in coefficients between IV and OLS are not systematic.

Table 3a: Returns to Schooling from IV – Male Employees 22-45 years (Instrument=1 if age in 1981 between 6 and 18 years)

Variable	IV: Reform	IV: Reform	IV: Reform
Years of schooling	0.077	0.043	0.042
	(3.2)	(1.3)	(1.3)
Experience	0.003	0.002	0.009
	(0.2)	(0.1)	(0.4)
Experience squared	0.0002	0.0002	-0.0001
	(0.3)	(0.3)	(0.3)
Standardized IALS score	-	0.204	0.051
		(2.9)	(0.5)
Stand. IALS score-years of schooling interaction	-	-	0.015
			(1.4)
Constant	5.66	5.94	5.84
	(14.1)	(12.7)	(12.7)
Centered R^2	0.158	0.183	0.188
N	586	586	586
First Stage:			
Shea's partial R^2	0.300	0.231	0.233
F-value	249.5	174.4	176.1
[p-value]	[0.000]	[0.000]	[0.000]
Over-identification Test:			
Hansen's J-statistic	Exactly Identified	Exactly Identified	Exactly Identified
Endogeneity Test:			
Durbin-Wu-Hausman statistic	0.64	0.45	0.33
[p-value]	[0.42]	[0.50]	[0.56]

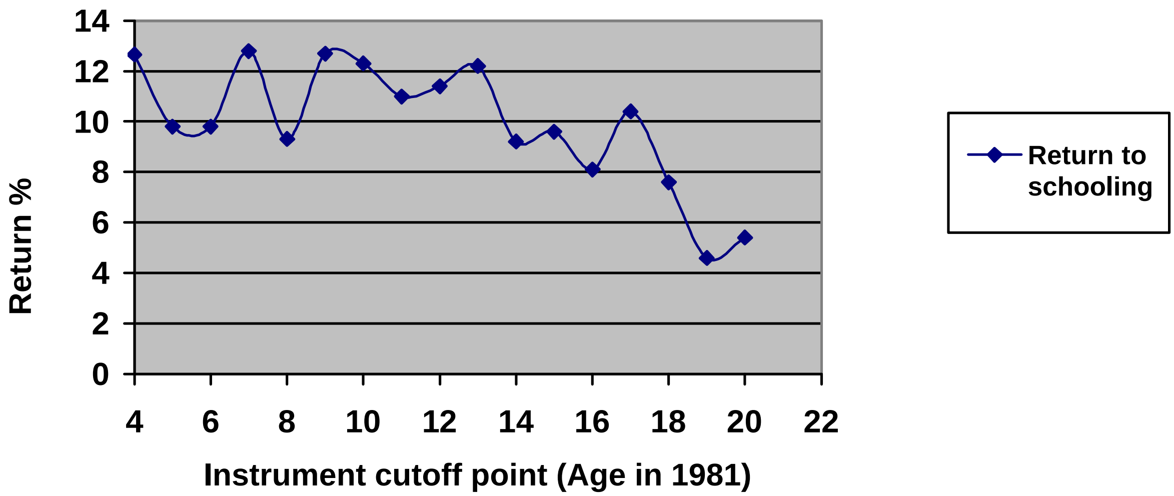
Note: t-values in parentheses

In Table A6a in the appendix we use the expanded age group (ages 6-18 in 1981) with the additional instrument (father at least secondary school). Here again, the effect of including the secondary school age students results in lower estimates for the return to schooling and higher estimates for the return to cognitive score compared to the results in Table 6. However, the return to schooling estimate is still higher and the return to cognitive score is lower than in Table 3a, given the composition of the treated group which consists of students with educated fathers. Once again based on the value of Hansen's J-statistic, the null hypothesis (that the instruments are appropriately uncorrelated with the disturbance process) is not rejected (p-values are between 7 and 19 percent).

Finally, we ask the question: what happens if we progressively expand the treated group to include students who, at the time of the reform were between the ages of 4 (20 years old in 1997) and 20 (36 years old in 1997)? That is, starting with a treated group of very young children in 1981, and progressively expanding the group one year at a time until age 20, tracing the changes coefficient estimates for schooling and cognitive skills. Suppose that such students, before deciding whether to switch schools (based on the comparison between expected benefits and costs) were enrolled in, say, municipal schools. Assuming that municipal schools on average provide lower quality schooling, switching to private-subsidized schools at a younger age (such as the beginning of primary school) should result in a higher and more homogeneous cognitive skill endowment by the end of the schooling period, compared to switching at a later age (such as during high school). We, therefore, would expect that as we progressively increase the instrument upper cutoff age, the treated group becomes less endowed in cognitive skills (because they have received most of their schooling before 1981) and less homogeneous in these skills.

As a result, as we add the marginal individual in the treated group, the return to cognitive skills will be increasing and the return to schooling will be decreasing. This is because part of a given estimate of the return to schooling from the Mincerian specification is due to the independent effect of cognitive skills. Given a group with less and more dispersed cognitive skills, a larger part of the Mincerian estimate of the return to schooling will be due the independent effect of cognitive skills. The opposite is true for a group endowed with more and less dispersed cognitive skills).

Chart 2: Returns to an additional year of schooling for different instrument cutoff points (Mincerian specification)



Charts 2 (based on the Mincerian specification), 3 (addition of IALS score) and 4 (addition of the educated father dummy as well as IALS score), confirm this hypothesis. In Chart 2, the Mincerian return is around 11-12 percent for the cohorts who in 1991 were of primary school age or lower and subsequently (by the end of basic education) declines sharply. In Chart 3, the return to schooling fluctuates at about 10 percent for the primary school cohorts and subsequently declines sharply; the opposite pattern is observed for the return to the cognitive score. With the last expansions of the instrument cutoff point, the return to schooling approaches zero, while one standard deviation increase in the cognitive score increases earnings by close to 30 percent. Finally, in Chart 4, the independent effect of having an educated father hovers at about a 20 percent increase in earnings (a little less for the primary school cohorts), while the magnitude and pattern of the returns to schooling and cognitive score are similar to those in Chart 3. One can also observe that the decline in the return to schooling estimate (increase in the return to cognitive score) coincides with the period between the end of the two cycles of compulsory basic education in Chile (ages 6-14) and the end of secondary education (ages 14-18).

Chart 3: Returns to an additional year of schooling and to one standard deviation of IALS score for different instrument cutoff points (Additional control: IALS score)

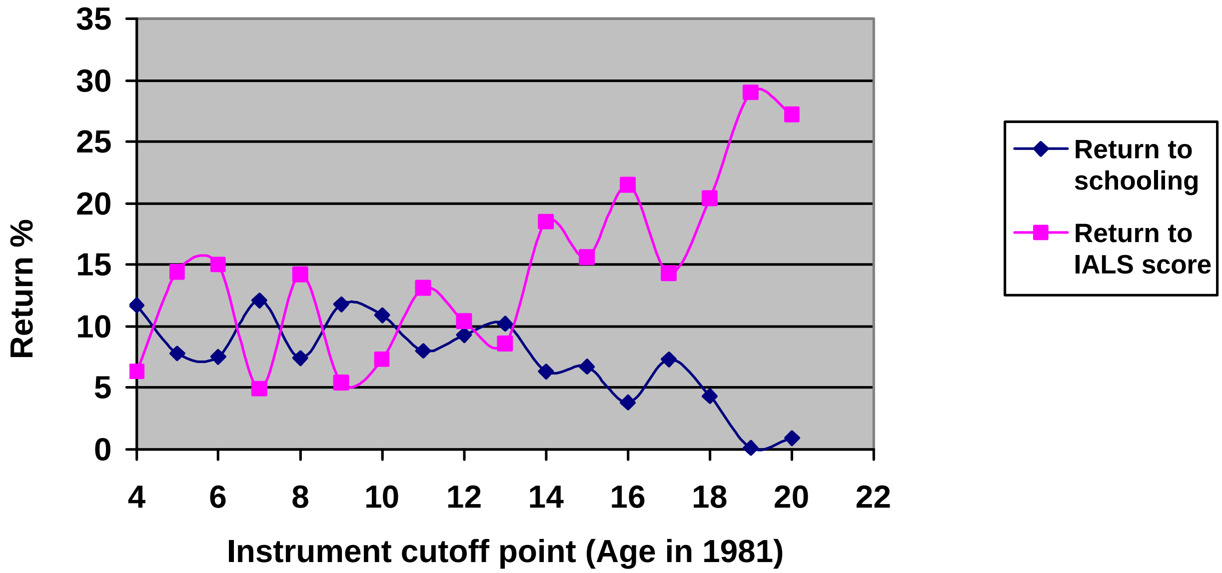
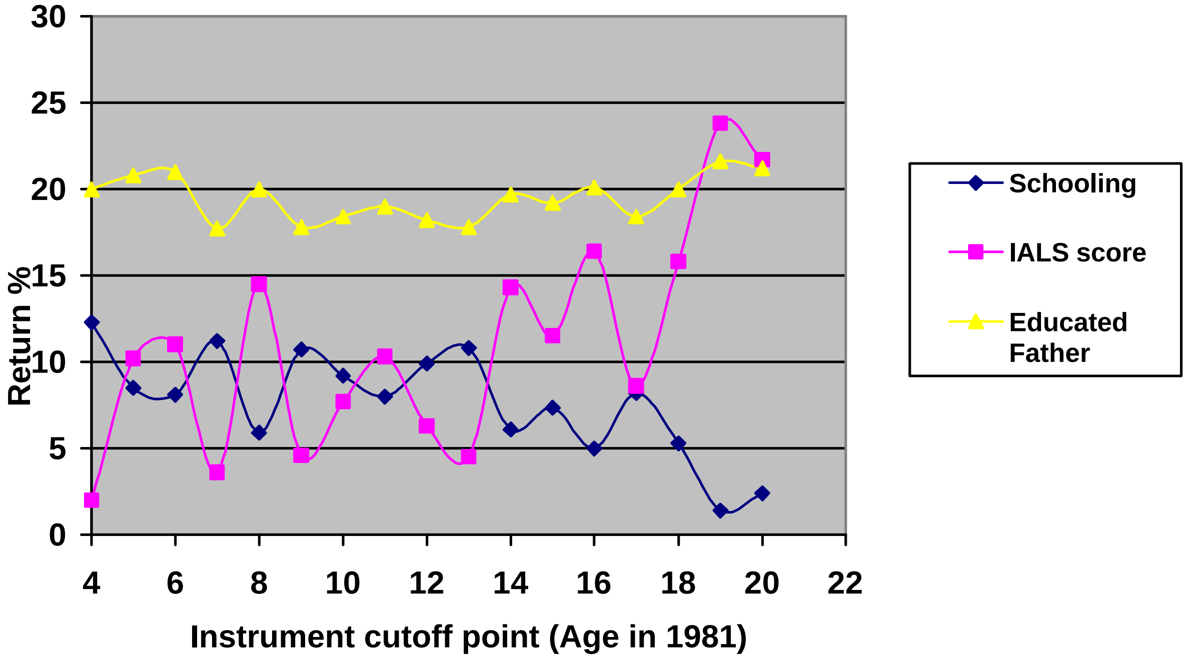


Chart 4: Returns to an additional year of schooling, one standard deviation of IALS score and educated father for different instrument cutoff points (Additional control: IALS score and Educated Father)



Concluding, the evidence suggests that the students who took advantage of the 1981 "voucher" reform came from better socioeconomic backgrounds, had higher cognitive skills and in 1981 they were enrolled in the early stages of schooling. However, this does not seem to have been the case for the older cohorts. The reform (capitation grants paid to schools and the opening of the education system to the private sector) facilitated the absorption of the large secondary school expansion, despite the decline in public spending for education. However, because of the secondary school expansion, lower ability students (from "middle class families or otherwise) may have been admitted into the system, students who had earlier received their basic education in public schools.

Conclusions

In the first part of this paper we estimate the return to investments in education and the return to cognitive skills across the ability distribution. We use data from the International Adult Literacy Survey (IALS), a carefully designed, innovative survey of adult populations, which goes beyond just measuring literacy capabilities, to assessing how these capabilities are applied to everyday activities. Such data allows the researcher to identify features of earnings determination that are typically only indirectly observed.

It is found that the inclusion of cognitive achievement, after conditioning for years of schooling and experience, reduces the return to schooling by about 25 percent on average. Further, it is shown that a one standard deviation increase in the score increases earnings by 15-20 percent, compared to about 35 percent when schooling and other covariates are eliminated from the equation. Therefore, there is an additional, indirect effect of cognitive achievement on earnings through schooling.

The quantile regression results are, however, much more informative. Before conditioning for years of schooling and experience, the combined direct and indirect effect of the cognitive achievement on earnings is consistently high (25 to 35 percent increase in earnings in response to one standard deviation increase in the score). However, once we condition for schooling and experience, the independent effect of cognitive achievement is positive and highly significant only up to the 75th quantile of earnings, but this effect all but disappears at the 90th quantile. When controlling for the independent effect of the cognitive achievement as well as its interaction with years of schooling, the independent effect of cognitive achievement is positive and particularly strong at the lowest earnings quantile. For quantiles 25-90 the picture is drastically different. The independent effect of the cognitive achievement at higher quantiles is insignificant. Instead, what matters is the earnings enhancing, complimentary relationship between the measure of cognitive ability and schooling.

We can therefore conclude that for those at the lowest earnings quantile, education qualifications alone do not contribute to earnings; rather cognitive ability (quality of skill) is the main contributor to higher earnings. On the other hand, those in high quantiles (therefore, those of higher ability) benefit much more from acquiring more schooling, and from the interaction of additional schooling with ability.

In the second part of the paper we use the school reform of 1981 to identify a binary instrument and estimate returns to schooling from IV, with and without controlling for cognitive ability. Given that ability bias needs to be dealt with, accounting for cognitive ability avoids the problem of using a possibly invalid instrument.

The 1981 capitation grant scheme facilitated the absorption of the pressure of secondary school expansion which resulted from the capitation grants paid to schools and the opening of the education system to the private sector, and resulted in large increases in student intake as well as a sharp decline in the dropout rate, especially in basic education. Overall, the reform improved the efficiency of the education system, possibly at the expense of equity.

The results suggest that those who in 1981 switched to private subsidized schools were mainly urban “middle class” students leaving public schools, possibly in search of better peer groups. We find evidence suggesting that for students with such characteristics, who switched during their basic education, a smaller part of the estimated return to schooling is due to classical ability bias and most of the estimated return can be attributed to additional schooling. This was not the case, however, for older cohorts (those in secondary education). The large secondary school expansion seems to have attracted a heterogeneous group students with lower cognitive ability, having earlier received their basic education in public schools. For this group of students a given increase in earnings is attributed to the return to cognitive ability rather than additional schooling.

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Appendix

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

Variable	Overall mean	10th	25th	50^{th}	75th	90th	99^{th}
Log (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: standard deviation in parentheses.
*Includes ten observations for those with earnings which exceed the 99^{th} percentile.

Table A2: Returns to Schooling (Male employees)

Dependent Variable: log of hourly wage	(1)	(2)	(3)	(4)
Years of schooling	-	0.113	0.087	0.082
		(14.9)	(8.9)	(8.3)
Experience	-	0.013	0.015	0.020
		(2.0)	(2.2)	(2.9)
Exp. Squared	-	-0.0000	-0.0000	-0.0002
		(0.1)	(0.2)	(1.2)
Standardized $Score_{IALS}$	0.342	-	0.153	0.004
	(12.8)		(4.2)	(0.1)
Standardized $Score_{IALS}$*years of schooling	-	-	-	0.018
				(3.0)
Constant	6.45	5.11	5.33	5.30
	(243.9)	(41.0)	(39.7)	(39.6)
R^2-adj.	0.158	0.215	0.230	0.237
N	861	861	861	861

Note: t-values in parentheses.

Table A3: Returns to Cognitive Achievement Using Quantile Regressions (Male employees)

Dependent Variable: log of hourly wage	Q10	Q25	Q50	Q75	Q90
Stad. $Score_{IALS}$	0.255	0.250	0.330	0.354	0.328
	(5.2)	(8.0)	(11.9)	(7.6)	(7.1)
Constant	5.69	6.05	6.45	6.86	7.33
	(124.2)	(182.7)	(221.1)	(150.3)	(171.4)
PseudoR^2	0.061	0.068	0.101	0.098	0.127

Note: t-values in parentheses.

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

Dependent Variable: log of hourly wage	Q10	Q25	Q50	Q75	Q90
Years of schooling	0.102	0.075	0.112	0.114	0.121
	(6.0)	(9.0)	(14.0)	(8.7)	(6.3)
Experience	0.023	0.017	0.027	0.002	0.004
	(1.7)	(2.1)	(3.6)	(0.2)	(0.4)
Exp. Squared	-0.0002	-0.0002	-0.0002	0.0003	0.0002
	(0.9)	(1.2)	(1.6)	(1.6)	(1.2)
Constant	4.39	5.12	5.01	5.65	5.86
	(17.1)	(36.3)	(37.4)	(27.8)	(20.4)
PseudoR^2	0.065	0.078	0.120	0.167	0.213

Note: t-values in parentheses.

Table A5: Returns to Schooling from OLS – Male Employees 22-45 years

Variable	(1)	(2)	(3)	(4)
Years of schooling	0.089	0.058	0.055	0.068
	(8.9)	(4.8)	(4.5)	(4.9)
Experience	0.000	0.001	0.011	0.011
	(0.0)	(0.1)	(0.7)	(0.7)
Experience squared	0.0002	0.0002	-0.0001	-0.0002
	(0.4)	(0.5)	(0.3)	(0.4)
Standardized IALS score	-	0.174	0.037	0.128
		(4.2)	(0.4)	(2.7)
Stand. IALS score-Years of schooling interaction	-	-	0.014	-
			(1.9)	
Father at least Upper Sec. education	-	-	-	0.194
				(2.3)
Constant	5.48	5.75	5.69	5.56
	(30.0)	(30.0)	(29.2)	(25.8)
Adj. R^2	0.156	0.179	0.182	0.207
N	586	586	586	490

Note: t-values in parentheses.

Table A6: Returns to Schooling from IV – Male Employees 22-45 years
(Instrument=1 if age in 1981 between 6 and 13 years)

Variable	IV: Reform + Educated father	IV: Reform + Educated father	IV: Reform + Educated father
Years of schooling	0.130	0.120	0.116
	(5.5)	(3.1)	(2.9)
Experience	0.025	0.024	0.029
	(1.2)	(1.2)	(1.3)
Experience squared	-0.0004	-0.0004	-0.0006
	(0.7)	(0.8)	(0.9)
Standardized IALS score	-	0.028	-0.022
		(0.3)	(0.2)
Stand. IALS score-years of schooling interaction		-	0.006
			(0.5)
Constant	4.80	4.91	4.92
	(12.5)	(9.5)	(9.7)
Centered R^2	0.175	0.185	0.190
N	490	490	490
First Stage:			
Shea's partial R^2	0.308	0.169	0.160
F-value	108.1	49.0	46.2
[p-value]	[0.000]	[0.000]	[0.000]
Over-identification Test:			
Hansen's J-statistic	2.09	1.96	1.71
[p-value]	[0.148]	[0.161]	[0.191]
Endogeneity Test:			
Durbin-Wu-Hausman statistic	5.38	2.53	1.93
[p-value]	[0.020]	[0.111]	[0.164]

Note: t-values in parentheses.

Table A6a: Returns to Schooling from IV – Male Employees 22-45 years
(Instrument=1 if age in 1981 between 6 and 18 years)

Variable	IV: Reform + Educated father	IV: Reform + Educated father	IV: Reform + Educated father
Years of schooling	0.099	0.067	0.063
	(3.8)	(1.9)	(1.7)
Experience	0.021	0.018	0.025
	(1.0)	(0.8)	(1.1)
Experience squared	-0.0005	-0.0005	-0.0007
	(1.0)	(0.9)	(1.1)
Standardized IALS score	-	0.142	0.043
		(1.8)	(0.4)
Stand. IALS score-years of schooling interaction	-	-	0.011
			(1.0)
Constant	5.23	5.57	5.55
	(12.3)	(10.7)	(10.7)
Centered R^2	0.190	0.205	0.210
N	490	490	490
First Stage:			
Shea's partial R^2	0.339	0.242	0.241
F-value	124.1	77.3	76.9
[p-value]	[0.000]	[0.000]	[0.000]
Over-identification Test:			
Hansen's J-statistic	3.29	2.15	1.70
[p-value]	[0.069]	[0.142]	[0.193]
Endogeneity Test:			
Durbin-Wu-Hausman statistic	9.36	7.14	8.79
[p-value]	[0.053]	[0.210]	[0.186]