Quality of Education in Chile

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1. Introduction and Goals

This study uses data from diverse sources to examine the factors that contribute to the attainment of cognitive skills in the Chilean population, both within the country and in comparison with other countries, and it also examines the impact that these cognitive skills may have on quality of life.

Chile's situation is privileged with regards to the goals of analyzing the determinants of quality of education, given the many sources of rich and reliable data on educational attainment of Chilean students, their background characteristics and school and teacher attributes. Some of these data have been previously used in a large number of analytical studies. Many of these studies have focused on documenting the low quality of Chilean education (e.g. Beyer, 2001; Eyzaguirre & Le Foulon, 2001) and several others have been concerned with testing the impact of public policies, especially the national voucher system, which has been the subject of numerous studies, with varying and sometimes conflicting results (Aedo & Sapelli, 2001; Bravo, Contreras & Sanhueza, 1999; Gallego, 2002; Hsieh & Urquiola, 2003; Larrañaga, 2004; McEwan & Carnoy, 1998; Mizala & Romaguera, 2000; Sapelli & Vial, 2002).

There are, however, several areas that have not been dealt with in currently available research studies, and on which we focus here. The most notable omission is the lack of studies that make use of the rich teacher data available through the national teacher evaluation system (DocenteMás), which constitute the more accurate existing measure of the actual teaching and learning processes that happen in the Chilean classroom. In previous studies, teacher effects have been either ignored completely, or they have been modeled based on attributes such as certification, training or years of experience. All of these characteristics are at best very distant proxies for teacher efficacy. However, data from the national teacher evaluation system contains much more direct measures of teacher performance, since teachers are required to submit a portfolio including lesson plans, assessment methods and a videotaped lesson, which are evaluated by trained staff in several dimensions of teaching quality (Manzi & Flotts, 2007). These teacher evaluation data have been available for some time now, and the way in which they were collected allows for the association of teaching quality with student achievement. The main goal of this study is to complement existing analyses with these data, in order to clarify the role that teachers and teaching play on the acquisition of cognitive skills in the Chilean school system.

School effects in general have not received enough attention in Chilean research. The majority of research dealing with school effects in Chile has focused on evaluating the efficacy of different types of schools, comparing for example, public with charter or private schools, or comparing different types of private schools (Aedo & Sapelli, 2001; Bravo, Contreras & Sanhueza, 1999; Gallego, 2002; Hsieh & Urquiola, 2003; Larrañaga, 2004; McEwan & Carnoy, 1998; Mizala & Romaguera, 2000; Sapelli & Vial, 2002). Some research has also concentrated on school effects having to do with intervention programs or public policies. Chay, McEwan and Urquiola (2004), for example, evaluated the impact of an intervention program for underperforming schools (P-900) and García (2006) used SIMCE data to assess the impact of the Full-time school schedule, while Contreras, Flores, Lobato & Macías (2005) used SIMCE data to estimate the impact of a policy of monetary incentives to schools and teachers. Finally, another set of studies has focused on compositional effects at the school level, especially on the effects of average school SES.

Thus, most of the research on school effects has largely ignored organizational variables such as school policies on selection, teacher teamwork, student organizations or supervision of teachers, focusing only on funding and composition. However, there are at least two reasons to examine the potential contribution of a different set of school variables. On one hand, finding relevant school variables that influence effectiveness may open the door to new public policies aimed at these sorts of processes. This would provide policy makers with a larger range of places to intervene, not limited to funding and other administrative issues. Secondly, we should examine other school variables since there are good reasons to assume that there are characteristics of schools, beyond their average SES and their funding source, that also influence their effectiveness. Wilms (2006), using data from PISA, finds that, although average SES accounts for 62.7% of the variability among schools and within countries, the remaining between-school variance is still significant, opening the question of what school variables, beyond student composition, influence a school's effectiveness. Some findings with Chilean data also suggest the need to examine the potential effects of a larger number of school attributes. Using TIMSS data, Ramírez (2002, 2004) attempted to explain mathematics achievement and learning rate in Chilean students, and found significant effects of the school's curriculum and the teachers' mathematics focus. Similarly, in analyses conducted by the Chilean Ministry of Education with PISA data (MINEDUC, 2003), some of the school characteristics measured by the PISA questionnaire –such as disciplinary climate and teacher expectations- were found to have a small but significant effect on student achievement. Additionally, these kinds of school attributes have been used in qualitative studies seeking to explain school effectiveness (e.g. Bellei, Muñoz, Pérez & Raczynski, 2003), also with results that suggest the need to take organizational variables into account in large-scale quantitative studies.

A third issue that will be addressed in this study is the quality of education in Chile in comparison with other countries. To date, Chile has participated in several international assessments, including TIMSS, PISA and LLECE. PISA 2000 data have been analyzed in detail by the Ministry of Education (Mineduc 2003, 2004), with a main focus on within-country results. Very recently, however, PISA 2006 data have been released, opening the possibility to examine the evolution of reading scores from 2000 to 2006. In this study we will use PISA 2006 data to compare Chile's performance with that of other Latin American countries, and also with all other countries taking the assessment, in the hope to illuminate some of the processes behind Latin American countries' poor performance in these tests.

Finally, the study attempts to examine the relations between quality of education and quality of life. Relations between education and quality of life indicators have usually relied on measures of the quantity of education, such as years of schooling or degree obtained. Studies that examine connections between quality of life and quality of education measured through attainment on achievement tests are rare and have only recently appeared. In Chile, such an endeavor presents many challenges, since existing data on tests such as SIMCE, PISA or TIMSS does not lend itself to be linked to any existing data on quality of life, which are usually collected at the household, not individual, level (for example, through the CASEN survey). An additional challenge is that most existing achievement-test data in Chile are not available for individuals old enough to have entered the labor market yet. There is however, one source of Chilean data that offers both cognitive skills scores and data on occupation and income on adults. This is the International Adult Literacy Survey (IALS) administered in Chile in 1998, which measures three dimensions of literacy skills in adults in the labor force who are 16 through 65 years old, and also collects other data such as labor participation, job qualifications, income, years of education, years of experience, years of training and parents' education. Here we will use this data to examine contributions of cognitive skills to those indicators of quality of life.

Goals of the study

1. To examine the effects of family, teacher and school variables on the results of Chilean schools in standardized achievement tests.

2. To identify country-level variables that may have an impact on quality of education in Chile, by comparing results on international tests (PISA) with those of similar countries.

3. To examine the impact of quality of education, measured through attainment on the Adult Literacy Survey, on occupational status, earnings and poverty.

2. Background: The Chilean Educational System

2.1 Providers, Coverage and Financing

The Chilean education system has suffered several changes in the last three decades. In 1980, elements of privatization and decentralization were introduced through a massive voucher system by which private schools were allowed to receive a state subsidy proportional to the number of students attending classes, as long as they met certain requirements. At the same time, administration of public schools was shifted from the Ministry of Education to local authorities (Municipalities). Up to 1980, the Ministry of Education was in charge of financing public education, establishing educational contents and investing in infrastructure. After the 1980s reform, the Ministry retained authority over educational contents and goals, and it was responsible for supervising the functioning of schools receiving voucher monies, while infrastructure and hiring decisions were delegated to local school administrators, both Municipal and private. As a consequence of the introduction of private operators into the system, a new group of schools was created –private-subsidized schools- and this increased the number of schools significantly in later years.

Starting in 1990, a significant increase in public investment in education was registered. This increase in investment had a clear impact on education coverage. According to Bellei (2005), between 1990 and 2000 this raised coverage in primary education from 93% to 98% and from 74% to 85% in secondary education. However, increases in educational quality, as measured by standardized tests, were not evident. It is likely that the increases in education coverage in those years have actually lowered average test scores, as children who would otherwise have been outside the school system begin to enter school. In spite of this, test scores have not experienced a drop. For example, in 2003 there was a 20% increment over the previous year in the number of students taking the SIMCE tests, but average SIMCE scores did not drop significantly

In 1991, the “Estatuto Docente” was created, establishing regulations for teacher salaries and protecting them from being fired from the Municipal system, tending to make the system more rigid. Also in 1991, a number of improvement programs were put in place that targeted schools which cater to the most vulnerable students (e.g. P900, MECE rural). In 1993 shared financing is introduced, which allowed private-subsidized and secondary Municipal schools to charge parents a fee in addition to the state voucher, provided this fee does not exceed a certain value. Primary Municipal schools can not use this system, and secondary Municipal schools can charge a fee only with the agreement of the majority of parents in the school.

2.2 Evaluations of the system.

The Chilean educational system is subject to several performance evaluations regularly, in three levels: student performance, school performance and teacher performance.

SIMCE.

Together with the national voucher system, a national evaluation of student performance was conceived that would provide parents with necessary information to make decisions about schools. In 1988, students in all Chilean schools begun to be tested with the SIMCE test (Sistema Nacional de Medición de la Calidad de la Educación), which was given in alternating years in 4^{th} and 8th grade, and later in 1994, also in 10^{th} grade. Until 1994, SIMCE results were delivered only in aggregates, they were given only to schools and Municipalities, and they were not comparable for different years. Starting in 1995, SIMCE results begun being publicized through the media, with the goal of contributing to its original purpose of providing information for parents to make decisions about schools.

In 1998, SIMCE suffered several changes. First, an effort was made to closely align SIMCE tests with the educational goals and contents specified in the new national curricula developed by the Ministry of Education. Together with this, the instruments were modified to include not only multiple choice questions, but also open questions destined to test more complex skills such as critical thinking or written expression. The complementary questionnaires for parents and school principals also suffered modifications with the goal of obtaining better quality information to associate with SIMCE results. In 2000 SIMCE starts publishing its results by groups of Socioeconomic status, in order to facilitate comparisons between schools that educate similar students. Later, results reports to schools also started to include examples of questions and their answers, in an effort to contribute to the improvement of teaching.

With regards to the instruments themselves, in 2000 IRT methodology was introduced, allowing comparisons across years, and making it possible to produce more accurate descriptions of different levels of performance, to measure with precision students with different skill levels, and to examine possible item bias.

DocenteMás.

The Chilean teacher evaluation system was established by law in 2004, when the old evaluation system was replaced by a formative evaluation system, to which each teacher must submit every four years, and the final result of which is expressed in four possible performance levels (outstanding, competent, basic and unsatisfactory). Standards for the evaluation system are based on the "Framework for Good Teaching" (Marco para la Buena Enseñanza) a document prepared by the Ministry of Education together with the Teachers Union and the Municipalities, which seeks to represent all the responsibilities that a teacher faces during his or her daily work and that have the potential to significantly impact their student's learning. This framework is organized in four domains. The domains are divided in several criteria that are finally represented by indicators. The fours domains are *preparation for teaching*, *creation of an adequate learning environment*, *teaching for all students* and *professional responsibilities*.

The evaluation is based on four instruments: a self-evaluation, a peer-evaluation, a report from supervisors and a portfolio. The peer evaluation consists of an extensive interview conducted by an external, trained interviewer. The portfolio includes two modules. The first module consists of written evidence about planning of teaching and the evaluation of students (a lesson plan and an assessment plan), and the other is a video of a 40-minute lesson. These two modules are scored on 8 dimensions (two for the planning of teaching, two for the student's assessment, one for the teacher's reflection about his/her performance, and three based on the video). Teachers who take the evaluation are also asked to answer a questionnaire, which is voluntary, which provides further information on their characteristics (sex, age, initial training, in-service training, years of experience, teaching load, among others).

SNED.

The National System of School Performance Evaluation (Sistema Nacional de Evaluación del Desempeño de los Establecimientos Educacionales, SNED) was implemented in 1996 and it offers monetary incentives to subsidized schools showing an outstanding performance in several dimensions. The system divides all subsidized schools (private and municipal) in *homogeneous* groups, so that they only compete with schools that educate similar students. The incentive is given to the top schools that educate 25% of the students in each geographical region and it is offered every two years. Ninety percent of the incentive given to a school is divided among all teachers in the school. Each teacher in turn receives an incentive that typically is half of their monthly salary or between 5 and 7% of their annual salary. The school principal determines the use of the remaining 10% (Vegas & Umansky, 2005).

The SNED score is calculated on the basis of five dimensions, constructed from four sources: a parents' questionnaire, a school form completed by school staff and validated by supervisors, statistical information provided by the Ministry, and the SIMCE results. The four dimensions included in the SNED index are the following:

Effectiveness.
This is the average school SIMCE score.
Improvement.
This is the mean difference between the SIMCE score of the current and previous year of the test.
Initiative.
This includes nine indicators from the SNED form, regarding the work of teachers both at the classroom and school level. Indicators are: use of small group activities; existence of complementary pedagogical activities; optional curricular activities; presence and regular functioning of a representative school management team; presence of a school council that includes parents, students, teachers and community representatives; student participation in extracurricular activities; extra-curricular activities with other schools; effective support of integrated students; establishment of pedagogical and management commitments and implementation of the Ministry's curriculum framework for preschool education). Some of these indicators are only applicable to some schools, e.g. those having to do with preschool education.
Working conditions and adequate functioning of the school.
This is the score assigned to the school by the ministry officials based on their compliance with Ministry regulations regarding administrative processes.
Equal opportunities.
This dimension includes information from the SNED form, the parents' questionnaire, and the Ministry's statistics. It includes the promotion rate, the retention rate, percentage of students with disability, presence of students with severe or multiple disability,

existence of a school integration project for students with special needs, absence of discriminatory practices, absence of undue sanctions for students.
Parent and teacher integration.
This dimension is based mostly on the SNED form, with only one indicator taken from the parents' questionnaire. Indicators are existence and functioning of the teacher's council, existence and functioning of the parents' association, existence and functioning of a representative students' council, the school includes parents in pedagogical and management decisions, the school analyzes and reports SIMCE results, the school analyzes and reports SNED results, the school propitiates the participation of parents.

In contrast to SIMCE data, the SNED results are not actively disseminated to the general public (although they are readily available in the Ministry's web page), so they can not be said to influence parents' decision when choosing a school. Although there have not been many impact evaluations of the SNED, Vegas and Umansky (2005) state that, taking into account all SNED evaluations, schools with higher probabilities of receiving the SNED incentives had higher average SIMCE scores, which suggests an impact of the system on student's outcomes.

3. Family, teacher and school effects on performance in standardized tests

3.1 Data and Analysis

3.1.1 Analytical approach

We used a multilevel approach in order to account for both individual and school contributions to SIMCE scores. In multilevel analysis, the individual score is explained using a variable representing a school, plus other covariates at both individual level and school level. The school factor can be considered as a fixed effect, so the interest is to estimate such a factor and to examine its contribution to explaining the variability of individual scores; if such a factor is viewed as a random effect, a correlation between individual scores by school is induced, and the between-school variability becomes a parameter of interest (for details, see Raudenbush & Bryk, 2002).

3.1.2 Variables

Overview

In this study, we used Language and Math scores in the 2005 4th grade SIMCE tests as our measure of quality of education. Individual variables were taken from the parent questionnaire that was sent home with children on the day they take the SIMCE test. Individual SES was calculated using a composite of mother's education, father's education and self-reported family income (variables were standardized and the average was obtained). This index produced higher correlations with SIMCE scores than any of the original variables (they go from 0,3 to around 0,4), and less than 1% of cases are lost.

School variables were obtained from four sources: aggregates of family variables, School variables from the SNED database, and school aggregates of the teacher evaluation system variables. School type (Municipal, private-subsidized or private), location (urban-rural) and class size were also taken into account. Finally, we also included a variable for the region of the school. Regions were grouped in four categories: North (regions I, II and III), Center (IV, V, VI and VII), South (VIII, IX, X, XI, XII) and Metropolitan (this is the reference category).

SNED variables

For the SNED variables, we constructed two separate indexes. An exploratory factor analysis of all indicators[1] included in the four process dimensions of the SNED revealed one predominant factor that explained 75% of the variance. However, in seeking to separate the effects of different aspects of school management, we forced a two-factor solution, which revealed a second factor which explained an additional 7% of the variance. Based on this analysis, we constructed two separate indexes of school management. The first index is *Management and Participation,* which includes the items Small group activities; Complementary pedagogical activities; Optional curricular activities; Presence and regular functioning of a representative school management team; Support networks and joint work with external institutions; Presence and functioning parents' association; Presence and

[1] Two variables were eliminated because they had data only for a small number of schools: Implementation of the Ministry's curricular framework for preschool education, and Presence of a student council.

functioning of teacher's council; Extra-curricular activities with other schools; Effective support of integrated students; Establishment of pedagogical and management commitments and Involvement of community members in pedagogical and management commitments. The second index is *Use of Information*, which includes two items taken from the parents' questionnaire: School uses and reports SIMCE results, and School uses and Reports SNED results.

3.1.3 Teacher evaluation variables

As for teacher evaluation data, we constructed and tested several possible indicators. Due to changes in the construction of the score after 2004, we decided to use only data from the years 2005 and 2006, which yielded a sample of around 25000 evaluated teachers. Since it was impossible to link the teacher information with class information (not all 4^{th} grade teachers had been evaluated in those years, which produced too many missing classes), we decided to treat this variable as a school variable, seeking to produce a measure of the quality of the stock of primary teachers in a school. We compared two measures: one of them included only 1^{st} to 4^{th} grade teachers, and the other included 5^{th} to 8^{th} grade teachers as well. In comparing these two measures, we found that the first one, including only 1^{st} to 4^{th} grade teachers, produced many schools with missing data and generated lower coefficients in the regression analyses. Therefore, we opted for the second one. The fact that the variable included 5^{th} to 8^{th} grade teachers in addition to those who teach 1^{st} to 4^{th} grade may imply that this variable does not necessarily represent the direct classroom-teaching effect of those teachers on student learning, since the dependent variable is 4^{th} grade achievement score, and 5^{th} to 8^{th} grade teachers presumably have not had an opportunity to teach these students. Thus, this variable must be interpreted as a general measure of the quality of primary teachers in a school, and the ways through which it may have an effect on students will be discussed in the results section.

As an additional measure of the teacher composition in schools, we also explored the use of a measure of dispersion of teacher quality, namely, the standard deviation in teacher scores within each school. However, this variable proved to be nonsignificant in all analyses and was therefore not taken into account.

Next, we had to decide whether to include the aggregate teacher evaluation score -a composite of the scores in the five instruments- or each score separately (Video, Lesson Plan, Self-evaluation, Peer Evaluation and Supervisor Evaluation). Previous analyses had shown that the five sub-scales behaved differently, and therefore we compared both alternatives. The five variables together explained more or less the same additional variance as the aggregate score, but when entering them separately, it was evident that this effect was explained mostly by two or three components, depending on the model. Therefore, we kept the five scores separate in order to identify the most relevant instruments. The score in each instrument has a minimum of 1 point and a maximum of 4.

Finally, we created two different teacher quality variables to be used in Language and Math analyses. While teachers from 1st to 4th grade teach all subjects to one class, teachers from 5th to 8th grade teach specific subjects. Therefore, we created one variable including 5th to 8th grade teachers of language, to be used in the analyses with the language SIMCE, and another variable including math teachers, to be included in the math SIMCE analyses.

We grouped the family and school variables in six groups to be entered successively into the regression analyses, to give rise to six different models. The groups were: Individual variables, Home processes variables, School structural variables, School Policy variables, School management variables and Teacher quality variables. Table 3.1 summarizes predictors included in SIMCE analyses for each of the three school samples.

Table 3.1: School and individual variables included in SIMCE analyses.

Variable	Description	Available for
	Outcome	
MATH	2006 SIMCE Mathematics score.	All schools
LANG	2006 SIMCE Language score.	
	Group 1: Individual variables	
SES	Composite of Father's education, Mother's education and family income.	All schools
MALE	Student is male.	
	Group 2: Home processes	
NPERSON	Categorical, Number of people living in the home: 2, 3, 4, 5, 6, 7, 8, 9, 10, more than 10, Nonresponse. Reference category is 2 people in the home).	All schools
BOOKS	Categorical, Number of books at home: No books, 1 through 5, 6 through 10, 11 through 30, 31 through 50; 51 through 100; more than 100, Nonresponse. (reference category is No Books).	
	Group 3: School variables	
TYPE	School type: Municipal, Private-Subsidized, Private (reference category is Municipal).	All schools
SCHSES	Average SES of school (school aggregate of individual SES variable).	
RURAL	Rural school.	
REGION	Categorical, Geographical Region: North, Center, South or Metropolitan (reference)	
	Group 4: School Policy	
SELECT	School selectivity. School selects students based on a test or behavior during a play session. Reference is Non-selection.	All schools
CLASSSIZE	School average of class size	
	Group 5: School Management	
MANAG_PART	Management and Participation Index created from SNED indicators.	Subsidized schools
INFO_USE	Information use Index created from SNED Indicators.	

Group 6: Teacher Quality		
TEVPLAN_L	Average score in Planning and Evaluation component of Teacher evaluation for 1st to 8th teachers, including Language teachers.	Municipal schools
TEVPLAN_M	Average score in Planning and Evaluation component of Teacher evaluation for 1st to 8th teachers, including Mathematics teachers.	
TEVVIDEO_L	Average score in Video component of Teacher evaluation for 1st to 8th teachers, including Language teachers.	
TEVVIDEO_M	Average score in Video component of Teacher evaluation for 1st to 8th teachers, including Mathematics teachers.	
TEVPEER_L	Average score in Peer Evaluation component of Teacher evaluation for 1st to 8th teachers, including Language teachers.	
TEVPEER_M	Average score in Peer Evaluation component of Teacher evaluation for 1st to 8th teachers, including Mathematics teachers.	
TEVSELF_L	Average score in Self Evaluation component of Teacher evaluation for 1st to 8th teachers, including Language teachers.	
TEVSELF_M	Average score in Self Evaluation component of Teacher evaluation for 1st to 8th teachers, including Mathematics teachers.	
TEVSUP_L	Average score in Supervisor Evaluation component of Teacher evaluation for 1st to 8th teachers, including Language teachers.	
TEVSUP_M	Average score in Supervisor Evaluation component of Teacher evaluation for 1st to 8th teachers, including Mathematics teachers.	

3.2 Determinants of test performance in Private, Private-subsidized and Municipal schools

3.2.1 Individual and school effects

We first conducted an analysis including all Chilean schools (233,338 students nested in 7,500 schools; 4,344 Municipal, 2,740 private-subsidized and 416 private). Four models were fitted for each outcome variable (Language and Math), each one adding one of the four groups of available variables. Table 3.2 summarizes the percentages of additional variance (over the variance in the null model) explained by each group of variables, at the between and within-school level. Table 3.3 shows coefficients for each variable in the final model.

Table 3.2: Summary of variance explained by each of the four models

		Percentage of original variance explained by each group of variables			
LANGUAGE	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**
Between-school	20,79%	48,08%	3,33%	12,98%	1,33%
Within-school	79,21%	3,32%	0,92%	-0,09%	0,00%
MATH	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**
Between-school	27,58%	49,51%	3,43%	10,17%	2,17%
Within-school	72,42%	3,74%	1,00%	0,00%	-0,04%

As table 3.2 shows, the unconditional between-school variance in language and math scores is around 21% and 28% respectively. Adding individual SES and gender explains almost half of the between-school variance for both language and math, with a positive effect of

SES and with males performing lower than females in language, and higher in math. Home processes (number of people living in the home and number of books) explain only a modest additional percentage of variance, although their effects are significant and in the expected direction: starting with five people in the home, a negative effect on individual scores is registered, while number of books in the home produces an increase of between two and six points associated to each category of book quantity. Adding structural school variables (mean SES, type of school, region and rural) explains an additional 13% of the between-school variance in language and an additional 10% in math. Average school SES shows a positive effect, even after accounting for individual SES (compositional effect), meaning that poor students do worse in poor schools than they would have done in schools with a more mixed SES composition. After adjusting for all other predictors in the model, schools located in the center and south of the country perform better than those located in the North and Metropolitan regions; private and private-subsidized schools show negative effects compared with municipal schools, and rural schools do better both in math and language. Finally, class size and whether the school selects students based on ability explain together 1,3% and 2,7% of the original between-school variance in language and math respectively. However, the effect of selection is larger than that of class size, and furthermore, the effect of class size in these models is positive (larger classes, higher scores), which is contrary to that popularly expected, but in agreement to recent research showing that class size may act as an endogenous variable that is indeed influenced by the cultural capital of the family and the performance of the school, since schools that have better results have higher demand from parents, which leads to bigger classes (Urquiola & Verhoogen, 2007).

Table 3.3: Coefficients for final model with all types of schools.

	Language			Math		
	Coefficient	**S.E.**	**t**	**Coefficient**	**S.E.**	**t**
Intercept	119.91	2.8631	41.88***	83.6132	3.2447	25.77***
Individual						
Male	-7.4419	0.2037	-36.54***	5.1853	0.2041	25.40***
SES	1.2743	0.01935	65.85***	1.4106	0.01934	72.93***
Home Processes						
3 people	-0.9914	0.7613	-1.30	-0.9541	0.7616	-1.25
4 people	-1.6168	0.7269	-2.22*	-0.2181	0.7272	-0.30
5 people	-4.6681	0.7332	-6.37***	-3.2357	0.7335	-4.41***
6 people	-6.6506	0.7572	-8.78***	-5.5844	0.7575	-7.37***
7 people	-8.5642	0.8067	-10.62***	-7.4176	0.8071	-9.19***
8 people	-9.1167	0.8956	-10.18***	-8.4289	0.8961	-9.41***
9 people	-9.7065	1.0345	-9.38***	-8.7131	1.0351	-8.42***
10 people	-11.5048	1.2099	-9.51***	-9.2106	1.2107	-7.61***
More than 10 people	-12.9810	1.0774	-12.05***	-11.3471	1.0783	-10.52***
People Missing	-9.4284	1.0090	-9.34***	-10.0043	1.0097	-9.91***
1 – 5 books	1.7173	0.4225	4.06***	2.7375	0.4231	6.47***
6 – 10 books	4.6446	0.4311	10.77***	6.0431	0.4318	14.00***
11 – 30 books	8.5815	0.4368	19.65***	10.8385	0.4375	24.77***
31 -50 books	11.2873	0.4916	22.96***	12.6822	0.4922	25.76***
51 - 100 books	13.9418	0.5469	25.49***	15.1498	0.5474	27.68***
> 100 books	16.2778	0.5940	27.41***	16.5616	0.5945	27.86***
Books missing	-2.7052	1.0080	-2.68**	-3.6593	1.0094	-3.63***
School Variables						
SchSES	1.2157	0.0026	20.17***	1.4735	0.06815	21.62***
Private – subsidized	-1.3547	0.5494	-2.47*	-4.5767	0.6309	-7.25***

	Language			Math		
	Coefficient	S.E.	t	Coefficient	S.E.	t
Private	-8.3960	1.4679	-5.72***	-11.5509	1.6846	-6.86***
North	-3.4666	0.9564	-3.62***	-6.2707	1.1192	-5.60***
Center	7.2421	0.5875	12.33***	5.7680	0.6827	8.45***
South	12.0068	0.5982	20.07***	7.6829	0.6946	11.06***
Rural	12.7774	0.7059	18.10***	9.6900	0.8091	11.98***
School Policy						
Selects	8.3912	0.7005	11.98***	10.3963	0.8184	12.70***
Class Size	0.09660	0.02634	3.67**	0.2656	0.03013	8.81***

In order to check for the equivalence of these results for rural and urban schools, we conducted separate analyses for each. Of our national sample of 7,500 schools, 57% (4,275) are located in urban areas, and they educate 88% of students. Conditions for rural and urban schools differ significantly, and therefore we considered relevant to test whether the effects observed for the total sample occur in both groups.

Tables 3.4 and 3.5 summarize explained variance and coefficients in final models for rural and urban groups. As shown in the tables, between-school variance in general is larger in urban schools than in rural schools, which is probably due to the fact that rural schools present a more homogeneous group in terms of SES. Additionally, models 1 through 4 explain less between-school variance in these schools than in those located in urban areas. Coefficients, however, are similar for both schools in individual and school variables. School selection continues to have a positive significant effect on both scores, and the same is observed for class size, except in the case of math scores in urban schools, where it is not significant.

Table 3.4: Summary of variance explained by each of the four models, by location.

LANGUAGE		Percentage of original variance explained by each group of variables			
Rural	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**
Between-school	14,44%	17,43%	2,95%	3,27%	1,66%
Within-school	85,56%	4,14%	1,16%	0,04%	-0,06%
Urban	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**
Between-school	22,13%	52,95%	3,83%	13,51%	1,83%
Within-school	77,87%	3,28%	0,90%	0,02%	0,01%
MATHEMATICS		**Percentage of original variance explained by each group of variables**			
Rural	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**
Between-school	21,82%	19,36%	4,24%	4,69%	0,30%
Within-school	78,18%	4,35%	1,18%	0,04%	0,00%
Urban	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**
Between-school	26,67%	50,54%	3,60%	12,85%	2,88%
Within-school	73,33%	3,71%	0,96%	0,04%	0,00%

Table 3.5: Coefficients for final model with all schools, by location.

	Language						Mathematics						
	Rural			Urban				Rural			Urban		
	Coeff	S.E.	t	Coeff	S.E.	t		Coeff	S.E.	t	Coeff	S.E.	t
Intercept	167.61	6.6537	25.19***	106.67	3.1472	33.89***	Intercept	127.43	7.5708	16.83***	72.6632	3.5084	20.71***
Individual							**Individual**						
Male	-9.1844	0.5679	-16.2***	-7.1771	0.2179	-32.9***	Male	2.3871	0.5868	4.07***	5.5894	0.2174	25.71***
SES	1.2958	0.05602	23.13***	1.2717	0.02062	61.68***	SES	1.5761	0.05756	27.3***8	1.3886	0.02052	67.66***
Home Processes							**Home Processes**						
3 people	1.2254	2.4945	0.49	-1.2074	0.7997	-1.51	3 people	2.6527	2.5769	1.03	-1.2906	0.7966	-1.62
4 people	1.6827	2.4029	0.70	-1.9673	0.7628	-2.58**	4 people	4.3010	2.4822	1.73	-0.6600	0.7598	-0.87
5 people	-1.8188	2.4182	-0.75	-4.9455	0.7696	-6.43***	5 people	1.0529	2.4979	0.42	-3.6193	0.7667	-4.72***
6 people	-4.4604	2.4739	-1.80	-6.8121	0.7958	-8.56***	6 people	-1.6274	2.5555	-0.64	-5.8941	0.7927	-7.44***
7 people	-5.6982	2.5827	-2.21*	-8.8109	0.8503	-10.4***	7 people	-3.1799	2.6682	-1.19	-7.7581	0.8471	-9.16***
8 people	-7.3610	2.8024	-2.63**	-9.1404	0.9468	-9.65***	8 people	-4.8945	2.8953	-1.69	-8.6184	0.9432	-9.14***
9 people	-10.5171	3.1543	-3.33***	-9.3680	1.0971	-8.54	9 people	-8.8145	3.2595	-2.70**	-8.3877	1.0929	-7.67***
10 people	-9.9501	3.6121	-2.75**	-11.5366	1.2861	-8.97***	10 people	-6.1243	3.7346	-1.64	-9.3549	1.2812	-7.30***
More than 10 people	-11.3702	3.5055	-3.24**	-12.9956	1.1322	-11.48***	More than 10 people	-9.2654	3.6236	-2.56*	-11.4026	1.1282	-10.11***
People Missing	-9.6783	2.8876	-3.35***	-8.9959	1.0872	-8.27***	People Missing	-8.5641	2.9839	-2.87**	-9.7642	1.0830	-9.02***
1 – 5 books	2.1774	0.8618	2.53*	1.5874	0.4844	3.28**	1 – 5 books	2.2965	0.8923	2.57*	2.8536	0.4826	5.91***
6 – 10 books	6.4516	0.9508	6.79***	4.2642	0.4875	8.75***	6 – 10 books	6.8969	0.9840	7.01	5.8820	0.4858	12.11***

	Language						Mathematics						
	Rural			Urban				Rural			Urban		
	Coeff	S.E.	t	Coeff	S.E.	t		Coeff	S.E.	t	Coeff	S.E.	t
11 – 30 books	12.0149	1.0654	11.28***	8.0945	0.4894	16.54***	11 – 30 books	12.9568	1.1021	11.76***	10.6033	0.4876	21.74***
31 -50 books	13.5669	1.4731	9.21***	10.9078	0.5407	20.17***	31 -50 books	14.2937	1.5209	9.40***	12.5268	0.5387	23.25***
51 - 100 books	13.0993	1.9222	6.81***	13.6952	0.5932	23.09***	51 - 100 books	15.2182	1.9837	7.67***	15.0759	0.5910	25.51***
> 100 books	20.0401	2.3443	8.55***	15.8295	0.6384	24.80***	> 100 books	18.5795	2.4191	7.68***	16.4206	0.6360	25.82***
missing	-4.9011	2.0714	-2.37*	-2.0437	1.1518	-1.77	missing	-8.0599	2.1451	-3.76***	-2.2753	1.1473	-1.98*
School Variables							**School Variables**						
SchSES	0.5201	0.1490	3.49***	1.3606	0.06584	20.66***	SchSES	0.6200	0.1690	3.67***	1.5862	0.07341	21.61***
Private – subsidized	-6.0511	1.2563	-4.82***	0.1440	0.6143	0.23	Private – subsidized	-11.92	1.4625	-8.15***	-1.6955	0.6949	-2.44*
Private	-5.9704	6.7999	-0.88	-6.5700	1.5529	-4.23***	Private	-8.3964	8.2318	-1.02	-8.1386	1.7462	-4.66***
North	-4.9495	3.4920	-1.42	-4.1000	0.9588	-4.28***	North	-8.7054	4.1334	-2.11*	-6.5053	1.0915	-5.96***
Center	6.0098	1.8818	3.19**	6.6565	0.6169	10.79***	Center	6.1615	2.2907	2.69**	4.4511	0.6978	6.38***
South	6.5248	1.9480	3.35***	13.2913	0.6296	21.11***	South	2.6349	2.3590	1.12	9.7652	0.7128	13.70***
School Policy							**School Policy**						
Selects	5.0474	4.3107	1.17	6.4013	0.6960	9.20***	Selects	10.8001	5.2943	2.04*	8.1635	0.7893	10.34***
Class Size	-0.2877	0.05710	-5.04***	0.2968	0.03039	9.77***	Class Size	-0.0613	0.06813	-0.90	0.4452	0.03395	13.11***

3.2.2 Socioeconomic differences in national educational measures

The previous section presented a detailed analysis of one of the national evaluation (SIMCE test for fourth graders, 2005). In this section we explore the stability of the effects of socioeconomic factors in other SIMCE evaluations (comparing different years and grades tested: 4th, 8th and 10th); and also in the University Selection Test (PSU), a mandatory test to enter all publicly funded universities and many private universities in Chile. Our focus in this section is on the role of individual and school socioeconomic factors in the context of the three types of schools in Chile (Municipal, Private-subsidized and Private). The publication of results stemming from these tests always includes direct comparisons of the average performance of the three types of schools, creating the public impression that the large gap in performance between them reflects differences in the quality of teachers and management of these schools. Other socioeconomic factors are typically ignored or only partially considered. In this section we compare models that attempt to decompose the between-school variance considering individual and school level socioeconomic factors as well as the type of schools.

It is important to consider that the two tests analyzed in this section have very different personal consequences for the examinees. Whereas the university selection test is the most consequential educational measure in Chile, SIMCE does not convey any personal consequences. This dimension of educational measures has been extensively investigated, showing that less-motivated examinees perform less well than their highly-motivated counterparts (see, among others, Kiplinger and Linn, 1993, 1996 and Wise and DeMars, 2005).

For these analyses we considered all recent available recent databases on these tests. For SIMCE, we examined tests administered between 2000 and 2006, with the exception of 2003 (this database was not available with all required information in time for this report). For the PSU test, tests administered between 2004 and 2007 were examined[2]. In each database an individual socioeconomic index was constructed considering: father educational level, mother educational level and self-reported family income. For the SIMCE, these variables were coded in different ways across years. Therefore, the socioeconomic index (SES) was built after standardizing each variable. The correlations across years between the three variables included in the index were over 0.6, with similar values. In the case of the PSU only the mother and father education were combined in the index, which was defined as the average of parents education. The individual SES index was then computed at the school level by averaging the SES of all students from each school.

Five types of multilevel models with a random effect at the school effect (intercept) were fitted:

Model 0: a baseline fully unconditional model (without covariates), which allowed us to estimate the between- and within-school variance.

Model 1: with type of school as a categorical fixed factor. This model estimates the observed gap among the three types of schools.

Model 2: with type of school and individual SES. This model indicates the amount of between and within school variance associated with the individual SES.

2 The PSU replaced the former test (PAA) in 2004. Therefore we decided to include only the results of the current test.

Model 3: with type of school, individual SES and School average SES.

Model 4: with individual SES and School average SES (without type of school). This model, when compared with model 3 indicates the role of school type when socioeconomic factors are included.

The results for the multilevel analyses corresponding to the 4 databases (SIMCE math, SIMCE language, PSU math and PSU language) are presented in Tables 3.6 to 3.9. Figures 3.1 to 3.4 show the coefficient of the fixed effect corresponding to the private school in comparison with public schools, estimated for Models 1, 2 and 3.

Table 3.6: Variance decomposition – SIMCE Math test

Model	Variance	2000 (8th)	2001 (10th)	2002 (4th)	2004 (8th)	2005(4th)	2006 (4th)
Model 0	Between	742.5	1545.4	820.7	774.1	821.5	875.4
	Within	1740.7	1867.1	2125	1723.63	2286.1	2299
	%betwen	29.9%	45.3%	27.9%	31.0%	26.4%	27.6%
Model 1	Between	450.5	764.1	513.4	473.5	585.1	628.4
	Within	1740.8	1867.3	2125.3	1723.8	2288.6	2301.7
	%betwen	39.3%	50.6%	37.4%	38.8%	28.8%	28.2%
	%intra	0.0%	0.0%	0.0%	0.0%	-0.1%	-0.1%
Model 2	Between	346.8	633	367.6	368.4	366.8	415.2
	Within	1704.5	1882.3	2069.6	1693.8	2208.6	2220.2
	%betwen	53.3%	59.0%	55.2%	52.4%	55.3%	52.6%
	Diff between	14.0%	8.5%	17.8%	13.6%	26.6%	24.4%
	%within	2.1%	-0.8%	2.6%	1.7%	3.4%	3.4%
Model 3	Between	267.5	395.4	285.5	277.9	309.4	358
	Within	1704.5	1882.6	2069.4	1693.8	2208.5	2220.7
	%betwen	64.0%	74.4%	65.2%	64.1%	62.3%	59.1%
	Diff between	10.7%	15.4%	10.0%	11.7%	7.0%	6.5%
	%within	2.1%	-0.8%	2.6%	1.7%	3.4%	3.4%
Model 4	Between	283.2	426.3	303.7	289.7	313.1	360.7
	Within	1704.4	1882.5	2069.2	1693.7	2208.7	2220.8
	%betwen	61.9%	72.4%	63.0%	62.6%	61.9%	58.8%
	%within	2.1%	-0.8%	2.6%	1.7%	3.4%	3.4%
	Diff between	2.1%	2.0%	2.2%	1.5%	0.5%	0.3%

The overall pattern of results could be summarized in the following way. First, the between-school variance is relatively large, ranging from about 25% to 47%. This percentage is quite stable across years within each grade, and shows some growth from 4th grade to secondary education, especially in the case of the mathematics test, indicating that school effects increase in importance as students move up in the school system. Second, a very large and stable percentage of between-school variance is accounted for by socioeconomic factors. In fact, model 4 shows that over 60% of this variance is explained by the combination of the individual and school socioeconomic factors. This result is consistent with PISA decomposition of variance, which shows that Chile is one of the countries with the largest percentage of between-school variance explained by socioeconomic factors. A third and very clear pattern is that the type of school *does not* explain a relevant proportion of between school variance once socioeconomic factor are considered. In fact, in all databases Model 3 and Model 4 explain a very similar proportion of between-school variance, with a slight increase (around 2%) when school type is included. These results reaffirm the extent of socioeconomic segregation in the Chilean educational system. Finally, as a consequence of this pattern of results, the gap between private and public schools changes dramatically depending on the inclusion or exclusion of socioeconomic factors: while the gap favors private schools when no socioeconomic control is involved, exceeding one standard deviation, this difference is importantly reduced when the individual socioeconomic index is considered and, even reverses when individual and school socioeconomic factor are considered. These last results are depicted in Figures 3.1 to 3.4.

Table 3.7: Variance decomposition – SIMCE Language test

Model	Variance	2000 (8th)	2001 (10th)	2002 (4th)	2004 (8th)	2005(4th)	2006 (4th)
Model 0	between	659.4	1013.5	803.6	686.7	690.2	697
	within	1846.7	1981.2	2097.3	2018.8	2173	2290.1
	%between	26.3%	33.8%	27.7%	25.4%	24.1%	23.3%
Model 1	between	389.8	544	498.1	426.9	482.4	425.9
	within	1846.9	1918.4	2097.7	2019.1	2175.3	2292.8
	%between	40.9%	46.3%	38.0%	37.8%	30.1%	38.9%
	%within	0.0%	3.2%	0.0%	0.0%	-0.1%	-0.1%
Model 2	between	288.7	439.7	353.6	319.8	294.3	301.3
	within	1816.5	1913.8	2042.5	1986	2102	2227.1
	%between	56.2%	56.6%	56.0%	53.4%	57.4%	56.8%
	Diff between	15.3%	10.3%	18.0%	15.6%	27.3%	17.9%
	%within	1.6%	3.4%	2.6%	1.6%	3.3%	2.8%
Model 3	between	219.4	302.2	273.6	241.2	249.4	281.1
	within	1816.2	1914.1	2042.4	1985.9	2102	2227.9
	%between	66.7%	70.2%	66.0%	64.9%	63.9%	59.7%
	Diff between	10.5%	13.6%	10.0%	11.4%	6.5%	2.9%
	%within	1.7%	3.4%	2.6%	1.6%	3.3%	2.7%
Model 4	between	240.1	346.9	296.5	264.7	253.6	281.1
	within	1815.9	1913.9	2042	1985.5	2102	2227.9
	%between	63.6%	65.8%	63.1%	61.5%	63.3%	59.7%
	%within	1.7%	3.4%	2.6%	1.6%	3.3%	2.7%
	Diff between	3.1%	4.4%	2.8%	3.4%	0.6%	0.0%

Table 3.8: Variance decomposition – PSU Math

Model	Variance	2004	2005	2006	2007
Model 0	**Between**	5329.2	5626.7	5731.8	5878.8
	Within	7017.6	7059.6	6976.9	6618.7
	%between	43.2%	44.4%	45.1%	47.0%
Model 1	**Between**	3165.3	3456.7	3330.1	3363.1
	Within	7017.3	7059.5	6976.8	6618.5
	%between	40.6%	38.6%	41.9%	42.8%
	%within	0.0%	0.0%	0.0%	0.0%
Model 2	**Between**	2617.8	2935.3	2821.1	2759.1
	Within	6929.7	6974.8	6891.4	6520.8
	%between	50.9%	47.8%	50.8%	53.1%
	Diff between	10.3%	9.3%	8.9%	10.3%
	%within	1.3%	1.2%	1.2%	1.5%
Model 3	**Between**	1593.7	1884.7	1820.5	1673.5
	Within	6929.0	6974.6	6891.0	6520.1
	%between	70.1%	66.5%	68.2%	71.5%
	Diff between	19.2%	18.7%	17.5%	18.5%
	%within	1.3%	1.2%	1.2%	1.5%
Model 4	**Between**	1629.1	1921.4	1835.9	1730.8
	Within	6928.6	6974.3	6891.2	6519.7
	%between	69.4%	65.9%	68.0%	70.6%
	%within	0.7%	0.7%	0.3%	1.0%
	Diff between	1.3%	1.2%	1.2%	1.5%

Table 3.9: Variance decomposition – PSU Language

Model	Variance	2004	2005	2006	2007
Model 0	**Between**	5847.1	5105.8	5514.5	5650.5
	Within	9242.0	7594.7	7223.6	6905.1
	%between	38.8%	40.2%	43.3%	45.0%
Model 1	**Between**	3305.1	3026.5	3186.9	3142.4
	Within	9241.6	7594.2	7223.3	6904.8
	%between	43.5%	40.7%	42.2%	44.4%
	%within	0.0%	0.0%	0.0%	0.0%
Model 2	**Between**	2569	2493	2661	2474
	Within	9091	7496	7132	6777
	%between	56.1%	51.2%	51.7%	56.2%
	Diff between	12.6%	10.4%	9.5%	11.8%
	%within	1.6%	1.3%	1.3%	1.8%
Model 3	**Between**	1549.8	1595.5	1673.5	1464.1
	Within	9088.9	7494.9	7130.9	6776.8
	%between	73.5%	68.8%	69.7%	74.1%
	Diff between	17.4%	17.6%	17.9%	17.9%
	%within	1.7%	1.3%	1.3%	1.9%
Model 4	**Between**	1606.2	1652.1	1736.4	1579.3
	Within	9088.7	7494.8	7130.8	6776.5
	%between	72.5%	67.6%	68.5%	72.1%
	%within	1.0%	1.1%	1.1%	2.0%
	Diff between	1.7%	1.3%	1.3%	1.9%

Figure 3.2. Private-Public school gap in SIMCE Math

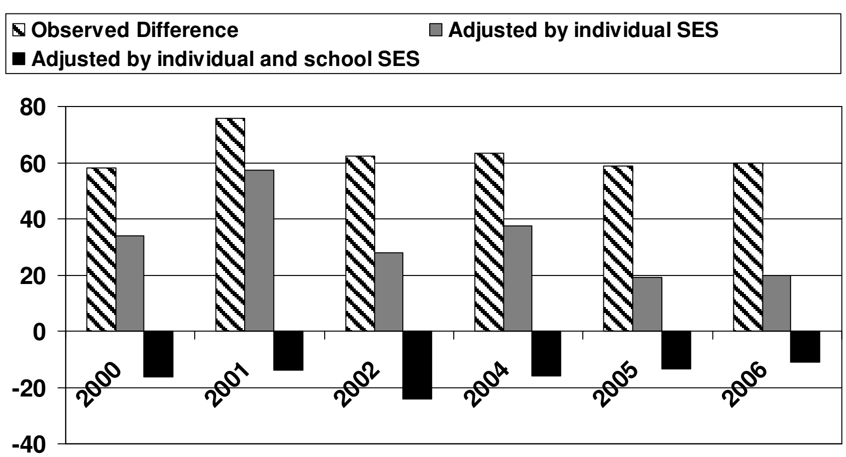


Figure 3.1. Private-Public school gap in SIMCE Language

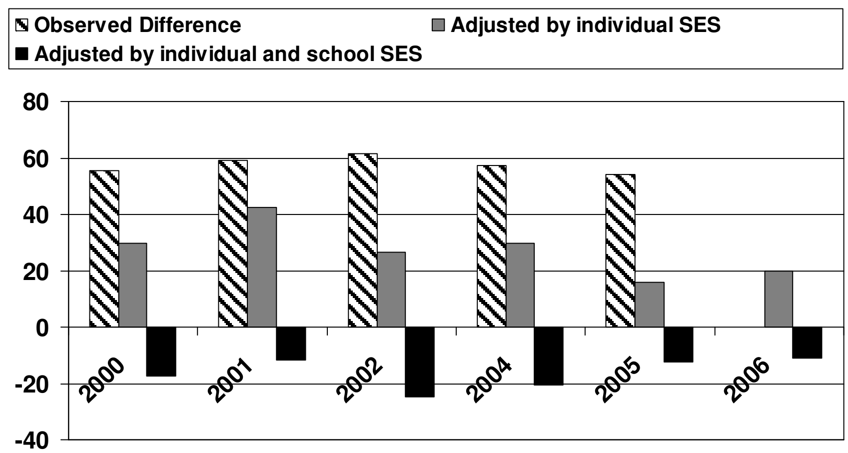


Figure 3.3. Private-Public school gap in PSU Math

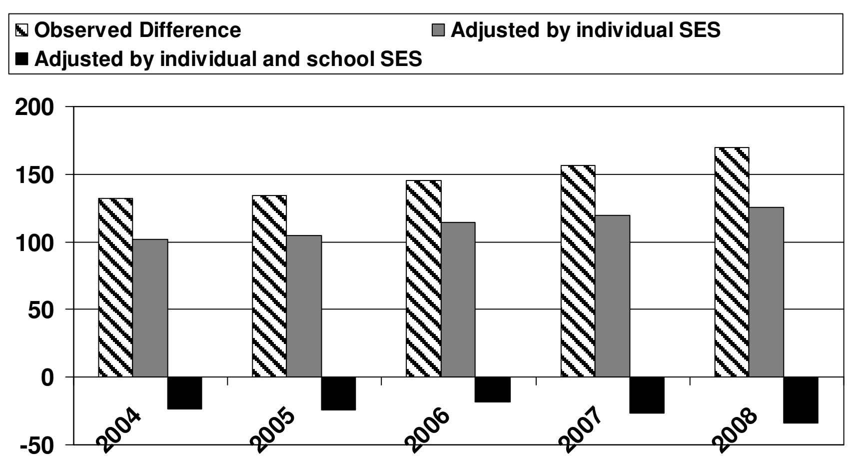
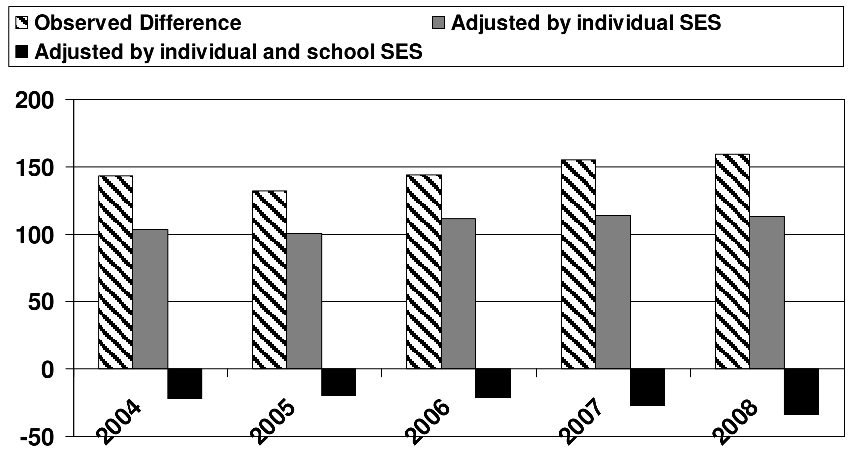


Figure 3.4. Private-Public school gap in PSU Language



3.3 Determinants of test performance in all subsidized schools

In this section we proceed with our analysis to look at more school variables that may be related to achievement scores, besides socioeconomic composition and type of school. This analysis is performed only of 4th grade SIMCE tests. In order to incorporate the management variables taken from the SNED evaluation system, we eliminated from subsequent analyses all private non-subsidized schools, which are not submitted to the SNED process. This leaves a universe of 7,084 schools (4,344 Municipal and 2,740 private-subsidized). However, some private-subsidized schools (N=243) do not have SNED scores, for reasons unclear. A comparison of schools with and without missing SNED data shows that schools with missing SNED scores have higher average SES, and higher average SIMCE scores in both in language and mathematics.

Table 3.9 summarizes the percentages of additional variance (over the variance in the null model) explained by each group of predictors, at the between- and within-school level, and

Table 3.11 shows coefficients for each variable in the final model. As Table 3.10 shows, the unconditional between-school variance in language and math scores, within subsidized schools, is around 17% and 23% respectively. Table 3.10 shows that the addition of the SNED variables contributes to explain an additional 1,5% of the original between-school variance in both language and math scores. Table 3.11, in turn, shows that this increment is associated with the significant positive effect of the variable "Information use", formed by two items from the parents questionnaire about whether the school analyses and uses SIMCE and SNED data.

Table 3.10: Summary of variance explained by each of the five models for subsidized schools

		Percentage of original variance explained by each group of variables				
LANGUAGE	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**
Between-school	17,49%	36,11%	4,26%	15,42%	1,62%	1,42%
Within-school	82,51%	3,44%	0,90%	-0,04%	0,00%	-0,04%
MATH	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**
Between-school	23,39%	39,39%	4,30%	10,96%	2,36%	1,53%
Within-school	76,61%	3,98%	0,97%	-0,04%	0,00%	-0,04%

Table 3.11: Coefficients for final model with subsidized schools.

	Language			**Math**		
	Coefficient	**S.E.**	**t**	**Coefficient**	**S.E.**	**t**
Intercept	119.36	3.0602	39.00***	82.6335	3.4684	23.82***
Individual						
Male	-7.5134	0.2158	-34.82***	5.3109	0.2174	24.43***
SES	1.2857	0.02024	63.52***	1.4333	0.02034	70.48***

	Language			Math		
	Coefficient	**S.E.**	**t**	**Coefficient**	**S.E.**	**t**
Home Processes						
3 people	-1.2067	0.8110	-1.49	-1.0755	0.8156	-1.32
4 people	-1.7231	0.7752	-2.22*	-0.2613	0.7795	-0.34
5 people	-4.8205	0.7821	-6.16***	-3.3912	0.7865	-4.31***
6 people	-6.7230	0.8075	-8.33***	-5.6560	0.8120	-6.97***
7 people	-8.7514	0.8596	-10.18***	-7.5286	0.8645	-8.71***
8 people	-8.9275	0.9528	-9.37***	-8.5300	0.9583	-8.90***
9 people	-10.5475	1.0970	-9.61***	-9.7072	1.1033	-8.80***
10 people	-11.4142	1.2730	-8.97***	-9.4749	1.2804	-7.40***
More than 10 people	-13.1164	1.1274	-11.63***	-11.6397	1.1342	-10.3***
People Missing	-9.4644	1.0615	-8.92***	-10.0041	1.0677	-9.37***
1 – 5 books	1.6889	0.4327	3.90***	2.6772	0.4356	6.15***
6 – 10 books	4.6367	0.4424	10.48***	6.0132	0.4454	13.50***
11 – 30 books	8.5197	0.4499	18.94***	10.8534	0.4529	23.96***
31 -50 books	11.2525	0.5128	21.94***	12.6042	0.5161	24.42***
51 - 100 books	13.9365	0.5849	23.83***	15.1294	0.5885	25.71***
> 100 books	16.2470	0.6588	24.66***	16.6873	0.6627	25.18***
Books missing	-3.3403	1.0471	-3.19***	-4.4385	1.0540	-4.21***
School Variables						
SchSES	1.1913	0.06369	18.70***	1.4438	0.07210	20.03***
Private – subsidized	-0.2048	0.5868	-0.35	-3.2614	0.6741	-4.84***
North	-3.6788	1.0130	-3.63***	-7.0684	1.1864	-5.96***
Center	6.9685	0.6305	11.05***	5.0099	0.7331	6.83***

	Language			Math		
	Coefficient	S.E.	t	Coefficient	S.E.	t
South	11.9006	0.6355	18.73***	6.8724	0.7381	9.31***
Rural	12.4995	0.7318	17.08***	9.0976	0.8397	10.83***
School Policy						
Selects	7.8961	0.7605	10.38***	10.0339	0.8899	11.27***
Class Size	0.004699	0.02889	0.16	0.1383	0.03313	4.18***
School Management						
InfoUse	0.08406	0.009555	8.80***	0.09217	0.01105	8.34***
ManagPart	0.001878	0.01018	0.18	0.01608	0.01165	1.38

Among private-subsidized schools, 43% are located in rural areas, and they educate 13% of children from all private subsidized schools. Separate analyses for rural and urban schools show some differences in both explained variances and the individual coefficients. These results are shown in tables 3.12 and 3.13. As with the sample of all types of schools, the between-school variance explained by individual variables is much less in rural schools than in urban schools (12 to 15% in rural and 42 to 40% in urban). In urban subsidized schools, the effects of selection continue to be positive and significant, while in rural schools it is much smaller and only significant for language scores. Similarly, the effect of class size, after excluding private non-voucher schools, remains positive only in urban schools, while the effect of the Use of Information index is significant in both.

Table 3.12: Summary of variance explained by each of the five models for subsidized schools, by location.

LANGUAGE		Percentage of original variance explained by each group of variables				
Rural	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**
Between-school	13,59%	11,79%	3,29%	3,53%	1,44%	0,24%
Within-school	86,41%	4,24%	1,17%	0,00%	-0,01%	0,00%
Urban	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**
Between-school	18,57%	41,53%	4,90%	16,22%	2,08%	1,79%
Within-school	81,43%	3,45%	0,89%	0,00%	0,01%	-0,01%
MATHEMATICS		**Percentage of original variance explained by each group of variables**				
Rural	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**
Between-school	20,84%	15,04%	4,54%	4,89%	0,34%	0,28%
Within-school	79,16%	4,47%	1,20%	0,05%	-0,01%	0,00%
Urban	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**
Between-school	22,25%	39,80%	4,56%	14,40%	3,25%	1,93%
Within-school	77,75%	3,94%	0,99%	0,01%	0,01%	0,00%

Table 3.13: Coefficients for final model with subsidized schools, by location.

	Language						Mathematics						
	Rural			Urban				Rural			Urban		
	Coeff	S.E.	T	Coeff	S.E.	t		Coeff	S.E.	t	Coeff	S.E.	t
Intercept	167.63	6.8124	24.61***	105.31	3.4084	30.90***	Intercept	126.94	7.7495	16.38***	70.9981	3.7951	18.71***
Individual							**Individual**						
Male	-9.1739	0.5735	-16.0***	-7.2352	0.2326	-31.11***	Male	2.4550	0.5938	4.13***	5.7658	0.2333	24.72***
SES	1.2856	0.05656	22.73***	1.2863	0.02167	59.36***	SES	1.5742	0.05825	27.02***	1.4135	0.02169	65.18***
Home Processes							**Home Processes**						
3 people	1.2715	2.5087	0.51	-1.4709	0.8576	-1.72	3 people	3.0484	2.5972	1.17	-1.5057	0.8587	-1.75
4 people	1.8078	2.4167	0.75	-2.1307	0.8187	-2.60**	4 people	4.7172	2.5017	1.89	-0.8032	0.8198	-0.98
5 people	-1.7897	2.4328	-0.74	-5.1467	0.8263	-6.23***	5 people	1.2980	2.5184	0.52	-3.8643	0.8275	-4.67***
6 people	-4.2254	2.4897	-1.70	-6.9415	0.8543	-8.13***	6 people	-1.1649	2.5773	-0.45	-6.0685	0.8554	-7.09***
7 people	-5.7874	2.6012	-2.22*	-9.0389	0.9122	-9.91***	7 people	-3.1863	2.6929	-1.18	-7.9107	0.9134	-8.66***
8 people	-7.0827	2.8281	-2.50*	-8.9686	1.0137	-8.85***	8 people	-4.4233	2.9282	-1.51	-8.8210	1.0151	-8.69***
9 people	-11.2729	3.1866	-3.54***	-10.209	1.1703	-8.72***	9 people	-9.0785	3.2999	-2.75**	-9.4794	1.1719	-8.09
10 people	-9.9399	3.6488	-2.72**	-11.455	1.3601	-8.42***	10 people	-6.1023	3.7809	-1.61	-9.6904	1.3619	-7.12***
More than 10	-11.5258	3.5250	-3.27**	-13.155	1.1902	-11.05***	More than 10	-9.4812	3.6513	-2.60**	-11.739	1.1922	-9.85***
People Missing	-9.1235	2.9053	-3.14**	-9.1237	1.1503	-7.93***	People Missing	-7.8675	3.0086	-2.62**	-9.8802	1.1519	-8.58***
1 – 5 books	2.2867	0.8652	2.64**	1.5137	0.4987	3.04**	1 – 5 books	2.2693	0.8977	2.53*	2.7967	0.4995	5.60***
6 – 10 books	6.5092	0.9547	6.82***	4.2180	0.5028	8.39***	6 – 10 books	6.8553	0.9901	6.92***	5.8588	0.5036	11.63***
11 – 30 books	12.1800	1.0727	11.35***	7.9638	0.5061	15.74***	11 – 30 books	12.7917	1.1120	11.50***	10.6261	0.5069	20.96***

	Language						Mathematics						
	Rural			Urban				Rural			Urban		
	Coeff	S.E.	T	Coeff	S.E.	t		Coeff	S.E.	t	Coeff	S.E.	t
31 -50 books	13.0546	1.4975	8.72***	10.8537	0.5654	19.20***	31 -50 books	13.9732	1.5492	9.02***	12.4559	0.5662	22.00***
51 - 100 books	13.0901	2.0027	6.54***	13.6540	0.6345	21.52***	51 - 100 books	15.2113	2.0713	7.34***	15.0522	0.6354	23.69***
> 100 books	20.8870	2.5185	8.29***	15.7027	0.7063	22.23***	> 100 books	20.0672	2.6043	7.71***	16.4828	0.7073	23.30***
missing	-5.0002	2.0788	-2.41*	-2.7769	1.2079	-2.30***	missing	-8.1341	2.1573	-3.77***	-3.1483	1.2096	-2.60**
School Variables							**School Variables**						
SchSES	0.5164	0.1521	3.39***	1.3379	0.07006	19.10***	SchSES	0.5918	0.1726	3.43***	1.5618	0.07803	20.02***
Private – subsidized	-5.6974	1.3179	-4.32***	1.4062	0.6549	2.15	Private – subsidized	-11.7003	1.5332	-7.63***	-0.2391	0.7389	-0.32
North	-5.4165	3.6086	-1.50	-4.4997	1.0188	-4.42******	North	-8.4064	4.2676	-1.97*	-7.5392	1.1570	-6.52***
Center	6.1698	1.9224	3.21**	6.2049	0.6669	9.30***	Center	6.1790	2.3405	2.64**	3.5000	0.7526	4.65***
South	7.0291	1.9836	3.54***	12.9323	0.6753	19.15***	South	3.0003	2.4031	1.25	8.6697	0.7623	11.37***
School Policy							**School Policy**						
Selects	5.5756	4.5778	1.22	5.6745	0.7576	7.49***	Selects	13.0191	5.6251	2.31*	7.4668	0.8579	8.70***
Class Size	-0.2866	0.06092	-4.70***	0.1851	0.03355	5.52***	Class Size	-0.0854	0.07293	-1.17	0.2932	0.03744	7.83***
School Management							**School Management**						
InfoUse	0.05087	0.02096	2.43*	0.08879	0.01050	8.45***	InfoUse	0.06579	0.02475	2.66**	0.09851	0.01188	8.29***
ManagPart	-0.02344	0.02037	-1.15	0.01847	0.01154	1.60	ManagPart	-0.0106	0.02368	-0.45	0.03048	0.01300	2.34*

3.4 Determinants of SIMCE scores in Municipal Schools

Finally, data on teacher's evaluation was taken into account, using only Municipal schools (the only ones with this kind of data). However, not all Municipal schools had teacher evaluation data, since in some schools teachers had submitted the evaluation prior to 2005 (not included here since it was not comparable), and in other schools, no primary teachers had taken the evaluation yet. Of the 4,344 schools, this yielded a sample of 3,743 schools for the language analysis and 3,697 schools for the math analysis. A comparison of schools with and without missing data shows that most schools with no teacher evaluation data are rural schools, since these have few teachers and therefore it is more likely that none of them had been evaluated in the specified years. With regards to SIMCE scores, schools with missing teacher evaluation data showed the same mathematics average scores, and a slightly but significantly higher language score (three more points on average).

Table 3.14 summarizes the percentages of additional variance (over the variance in the null model) explained by each group of variables, at the between- and within-school level. Table 3.14 shows coefficients for each variable in the final model. As Table 3.13 shows, the unconditional between-school variance in language and math scores, within Municipal schools, is around 12% and 15% respectively. Table 3.14 shows that the addition of teacher evaluation data at the school level contributes to explain an additional 1,76% of the original variance in language and an additional 2,76% in math, after all other predictors have been taken into account. Table 3.15 shows that this increment is associated with the significant positive effects of three of the five teacher evaluation components: peer evaluation, video and lesson plan.

Table 3.14: Summary of variance explained by each of the six models for municipal schools.

		Percentage of original variance explained by each group of variables					
LANGUAGE	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**	**Teacher Quality**
Between-school	12,35%	10,87%	4,06%	21,53%	0,47%	1,60%	1,76%
Within-school	87,65%	4,29%	1,00%	-0,04%	0,00%	0,02%	0,01%
MATH	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**	**Teacher Quality**
Between-school	15,37%	17,62%	4,19%	8,41%	1,03%	1,90%	2,76%
Within-school	84,63%	4,91%	1,21%	-0,01%	-0,06%	0,00%	0,01%

Table 3.15: Coefficients for final model with municipal schools.

	Language			Math		
	Coefficient	**S.E.**	**T**	**Coefficient**	**S.E.**	**t**
Intercept	93.8480	6.7115	13.98***	51.9540	7.7008	6.75***
Individual						
Male	-8.4755	0.3046	-27.83***	4.7565	0.3144	15.13***
SES	1.3905	0.02831	49.11***	1.6189	0.02916	55.51***
Home Processes						
3 people	-0.3850	1.2119	-0.32	-0.1233	1.2485	-0.10
4 people	-0.9091	1.1590	-0.78	0.5258	1.1940	0.44
5 people	-4.1622	1.1666	-3.57***	-2.9567	1.2019	-2.46*
6 people	-5.7900	1.1958	-4.84***	-5.3135	1.2321	-4.31***
7 people	-8.3221	1.2568	-6.62***	-7.3989	1.2949	-5.71***
8 people	-7.6328	1.3647	-5.59***	-8.1681	1.4078	-5.80***
9 people	-9.8152	1.5293	-6.42***	-9.8780	1.5744	-6.27***
10 people	-11.8018	1.7366	-6.80***	-10.2174	1.7922	-5.70***
More than 10	-12.4437	1.5383	-8.09***	-11.2144	1.5870	-7.07***
Missing	-9.1299	1.4890	-6.13***	-11.0023	1.5346	-7.17***

	Language			Math		
	Coefficient	S.E.	T	Coefficient	S.E.	t
1 – 5 books	1.9814	0.5357	3.70***	2.3162	0.5530	4.19***
6 – 10 books	5.4350	0.5582	9.74***	6.1768	0.5763	10.72***
11 – 30 books	9.3595	0.5811	16.11***	11.5194	0.5998	19.21***
31 -50 books	12.7774	0.7095	18.01***	14.1593	0.7319	19.35***
51 - 100 books	15.1114	0.8706	17.36***	16.2969	0.8984	18.14***
> 100 books	15.8977	1.0317	15.41***	16.4000	1.0621	15.44***
Missing	-4.5362	1.3386	-3.39***	-6.1351	1.3810	-4.44***
School Variables						
SchSES	0.9856	0.1188	8.30***	1.0678	0.1350	7.91***
North	-2.2093	1.3728	-1.61	-6.4766	1.6035	-4.04***
Center	7.1864	0.9399	7.65***	4.1070	1.1057	3.71***
South	12.1811	0.9540	12.77***	6.3402	1.1160	5.68***
Rural	10.0302	0.9239	10.86***	7.1746	1.0708	6.70***
School Policy						
Selects	5.3517	2.1816	2.45*	7.0867	2.5996	2.73**
Class Size	-0.1939	0.04327	-4.48***	-0.06739	0.05009	-1.35
School Management						
InfoUse	0.06936	0.01289	5.38***	0.07952	0.01502	5.29***
managPart	-0.00918	0.01528	-0.60	0.008270	0.01759	0.47
Teacher Quality						
TevSelf	1.3474	0.8583	1.57	1.2313	0.9952	1.24
TevPeer	3.5382	0.6929	5.11***	5.4370	0.7990	6.80***
TevSup	0.6047	0.6344	0.95	0.6115	0.7377	0.83
TevPlan	3.7416	1.1713	3.19**	6.2868	1.3972	4.50***
TevVideo	4.5826	1.2799	3.58***	4.2734	1.5834	2.70***

Separate analyses for schools located in rural and urban areas show small differences between the models. These analyses are shown in tables 3.16 and 3.17.

Table 3.16 shows that school variables such as region or average SES explain less between-school variance among rural schools than urban schools, but that the effects of teacher quality are larger in rural schools. In these schools, teacher quality variables explain approximately an additional 4% of between-school variance for both math and language, while in urban schools, these variables only account for one to two percent of additional variance. In Table 3.17 we observe that the effects of the five components of teacher evaluation are not the same across locations. The only effect that appears consistently in language and math in both rural and urban schools is that of Peer Evaluation. As for the effects of the Lesson Plan and Video Modules, which were both significant in the model with all schools, none of them is significant in urban schools.

Table 3.16: Summary of variance explained by each of the five models for Municipal schools, by location.

LANGUAGE		Percentage of original variance explained by each group of variables					
Rural	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**	**Teacher Quality**
Between-school	12,26%	3,76%	2,16%	4,16%	2,95%	0,41%	4,04%
Within-school	87,74%	4,84%	1,19%	-0,04%	0,02%	-0,01%	0,19%
Urban	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**	**Teacher Quality**
Between-school	12,62%	22,19%	4,91%	18,69%	0,07%	2,37%	1,46%
Within-school	87,38%	4,26%	0,99%	-0,03%	0,00%	0,03%	0,02%

MATH		Percentage of original variance explained by each group of variables					
Rural	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**	**Teacher Quality**
Between-school	17,50%	8,75%	3,67%	1,68%	0,37%	0,38%	3,96%
Within-school	82,50%	5,08%	1,33%	-0,01%	0,02%	-0,01%	-93,53%
Urban	**Total Var**	**Individual**	**Home processes**	**School Variables**	**School Policy**	**School Management**	**Teacher Quality**
Between-school	14,61%	22,59%	4,74%	12,42%	0,36%	2,70%	2,13%
Within-school	85,39%	4,94%	1,19%	-0,02%	0,00%	0,01%	0,00%

Table 3.17: Coefficients for final model with Municipal schools, by location.

	Language							**Mathematics**					
	Rural			**Urban**				**Rural**			**Urban**		
	Coeff	**S.E.**	**t**	**Coeff**	**S.E.**	**t**		**Coeff**	**S.E.**	**t**	**Coeff**	**S.E.**	**t**
Intercept	127.08	10.9665	11.59***	72.9039	8.6427	8.44***	Intercept	82.1080	12.2350	6.71***	30.4977	9.7535	3.13**
Individual							**Individual**						

	Language							Mathematics					
	Rural			Urban				Rural			Urban		
	Coeff	S.E.	t	Coeff	S.E.	t		Coeff	S.E.	t	Coeff	S.E.	t
Male	-9.5281	0.6784	-14.04***	-8.1992	0.3437	-23.86***	Male	1.5529	0.6987	2.22*	5.5475	0.3514	15.78***
SES	1.3508	0.06713	20.12***	1.3997	0.03151	44.42***	SES	1.6602	0.06889	24.10***	1.6095	0.03217	50.03***
Home Processes													
3 people	4.4840	2.9756	1.51	-1.1387	1.3404	-0.85	3 people	4.3526	3.0477	1.43	-0.8684	1.3693	-0.63
4 people	5.8179	2.8719	2.03*	-2.0993	1.2791	-1.64	4 people	6.6369	2.9395	2.26*	-0.6255	1.3068	-0.48
5 people	2.5431	2.8920	0.88	-5.3321	1.2872	-4.14***	5 people	3.1564	2.9598	1.07	-4.0985	1.3152	-3.12**
6 people	-0.08320	2.9604	-0.03	-6.7519	1.3199	-5.12***	6 people	-0.1037	3.0310	-0.03	-6.2217	1.3486	-4.61***
7 people	-2.4640	3.1001	-0.79	-9.2552	1.3880	-6.67***	7 people	-2.1353	3.1767	-0.67	-8.3344	1.4181	-5.88***
8 people	-0.9480	3.3663	-0.28	-8.7687	1.5089	-5.81***	8 people	-0.08661	3.4546	-0.03	-9.6154	1.5415	-6.24***
9 people	-6.1697	3.8167	-1.62	-10.7251	1.6840	-6.37***	9 people	-6.7659	3.9114	-1.73	-10.3650	1.7200	-6.03***
10 people	-7.5548	4.3373	-1.74	-12.6080	1.9176	-6.57***	10 people	-4.8808	4.4478	-1.10	-11.0727	1.9585	-5.65***
More than 10	-6.7885	4.2215	-1.61	-13.4272	1.6755	-8.01***	More than 10	-8.7014	4.3394	-2.01*	-11.8205	1.7119	-6.90***
People Missing	-3.9370	3.4631	-1.14	-9.8772	1.6721	-5.91***	People Missing	-5.3725	3.5476	-1.51	-11.9960	1.7080	-7.02***
1 – 5 books	2.3760	1.0307	2.31*	1.9859	0.6324	3.14***	1 – 5 books	1.8727	1.0625	1.76	2.4811	0.6461	3.84***
6 – 10 books	6.6746	1.1295	5.91***	5.1632	0.6504	7.94***	6 – 10 books	6.3973	1.1640	5.50***	6.1607	0.6647	9.27***
11 – 30 books	11.9403	1.2668	9.43***	8.9123	0.6682	13.34***	11 – 30 books	12.8645	1.3062	9.85***	11.3166	0.6827	16.58***
31 -50 books	13.0625	1.7877	7.31***	12.5543	0.7958	15.78***	31 -50 books	14.6319	1.8402	7.95***	14.0995	0.8133	17.34***
51 - 100	15.3699	2.4465	6.28***	14.8857	0.9587	15.53***	51 - 100	16.1247	2.5303	6.37***	16.3438	0.9798	16.68***

	Language						Mathematics						
	Rural			Urban				Rural			Urban		
	Coeff	S.E.	t	Coeff	S.E.	t		Coeff	S.E.	t	Coeff	S.E.	t
books							books						
> 100 books	21.6903	3.1943	6.79***	15.0419	1.1198	13.43***	> 100 books	20.0370	3.2512	6.16***	16.0644	1.1434	14.05***
missing	-7.5759	2.5605	-2.96***	-3.3367	1.5825	-2.11*	missing	-10.742	2.6461	-4.06***	-4.2166	1.6150	-2.61**
School Variables							**School Variables**						
SchSES	0.3617	0.2000	1.81	1.3546	0.1486	9.12***	SchSES	0.3938	0.2209	1.78	1.4802	0.1680	8.81***
North	-4.8479	4.1739	-1.16	-3.4553	1.4160	-2.44*	North	-3.5663	4.6351	-0.77	-8.4107	1.6139	-5.21***
Center	4.6770	2.1090	2.22*	6.9683	1.0796	6.45***	Center	6.1161	2.5004	2.45*	2.2880	1.2315	1.86
South	5.5051	2.2192	2.48*	14.1569	1.0652	13.29***	South	2.2834	2.6183	0.87	8.6706	1.2128	7.15***
School Policy							**School Policy**						
Selects	-42.7040	11.9581	-3.57***	3.8015	2.1756	1.75	Selects	-36.380	13.5457	-2.69**	5.6438	2.5001	2.26*
Class Size	-0.3995	0.07104	-5.62***	-0.03379	0.05760	-0.59	Class Size	-0.2012	0.08287	-2.43*	0.04331	0.06490	0.67
School Management							**School Management**						
InfoUse	0.04396	0.02405	1.83	0.07728	0.01524	5.07***	InfoUse	0.0530	0.02788	1.90	0.09205	0.01733	5.31***
ManagPart	-0.03991	0.02514	-1.59	0.03523	0.01958	1.80	ManagPart	-0.0162	0.02875	-0.57	0.03606	0.02219	1.63
Teacher Quality							**Teacher Quality**						
TevSelf	0.4647	1.3135	0.35	2.7783	1.1842	2.35*	TevSelf	0.1357	1.4379	0.09	2.4851	1.3807	1.80
TevPeer	3.4178	1.0547	3.24**	3.4672	0.9385	3.69***	TevPeer	5.8370	1.1941	4.89***	4.8382	1.0701	4.52***
TevSup	1.8374	0.9747	1.89	-0.5820	0.8679	-0.67	TevSup	2.5508	1.1174	2.28*	-1.3695	0.9763	-1.40
TevPlan	7.2692	1.7558	4.14***	2.0852	1.6410	1.27	TevPlan	9.0267	2.1052	4.29***	3.7057	1.8540	2.00*
TevVideo	5.0958	1.9786	2.58***	3.4771	1.8205	1.91	TevVideo	2.9215	2.3713	1.23	6.5922	2.1203	3.11**

3.5 Determinants of teacher evaluation results

The previous analysis shows that schools where the team of primary teachers as a whole has a higher average score on three of the components of the teacher evaluation (Video, Lesson Plan and Peer Evaluation), tend to obtain higher results in language and math, especially in Rural schools, but also in Urban schools for some of these instruments. It therefore becomes relevant to ask what school and/or teacher characteristics predict teachers' score on these components of the teacher evaluation system.

3.5.1 School determinants of teacher score

First, we fitted a multilevel unconditional model for teachers' scores on the different instruments, in order to determine whether these scores are explained in part by the school in which teachers work. The unconditional model revealed that the school only explains teacher score in the Peer Evaluation component (between-school variance of this score is 27%), while the impact of the school on the Video and Lesson Plan performance is very small: only 8% and 10% of the variance, respectively, lies between schools. Since it was possible that low between-school variance was caused by small numbers of teachers in many schools, we re-run the analyses only with schools that have 5 or more teachers with valid teacher evaluation scores, but the results were virtually the same. This suggests that the best teachers (according to the two portfolio modules) are not necessarily grouped in specific schools; while on the other hand, the best teachers according to the peer evaluation results do tend to be grouped in schools. As a follow-up, we conducted an analysis of school determinants of the Peer Evaluation scores (table 3.18). This analysis showed that these scores are not associated to the school's rurality or its average SES, but that teachers in center and South-region schools tend to obtain better scores than their peers in the Metropolitan Region. This model explains 12% of the between-school variance in peer-evaluation scores.

Table 3.18: School effects on Peer Evaluation scores

	Coefficient	S.E.	t
Intercept	2.7300	0.1104	24.72***
SchSES	0.001252	0.002330	0.54
Rural	0.01275	0.01778	0.72
North	0.04728	0.03360	1.41
Center	0.09430	0.02198	4.29***
South	0.2935	0.02134	13.75***

As it turns out, it is very common that the same interviewer interviews several teachers in one school, which would explain the high percentage of variance explained by the school. It is likely, then, that this is not actual between-school variance, but rather, between-*interviewer* variance. Although this may cast doubts on the validity of the peer interviewer scores, the fact remains that they are a significant predictor of a school's average SIMCE scores, after adjusting for all other covariates in the model, and a rather consistent one across subjects (language and math) and rural or urban location. This may show that, although interviewers have biases, these are not enough to invalidate their judgment of the teacher they are evaluating.

The low between-school variance in the Video and Lesson Plan components of the teacher evaluations, and the fact that the high between-school variance of Peer-evaluation can be explained by the high between-interviewer variance, suggests that there are no school factors that influence the grouping of similar teachers in specific schools. This contributes to dismissing concerns about possible teacher selection bias; for example, that schools which select the best students also select the best teachers, or that schools that have better administrative practices or other high-quality policies unrelated to teaching also select good teachers, therefore confounding teacher effects with other indirect school effects. If this were the case, it is reasonable to expect that between-school variability of teacher scores would be higher than 10%. These results are consistent with the fact that Municipal school in Chile have very little decision-making power with regards to hiring and firing teachers, since their control over these matters are limited by the Estatuto Docente, which regulates salaries and the possibility of firing teachers.

3.5.2 Individual determinants of teacher score

Together with the materials for the mandatory teacher evaluation, the teacher evaluation system also distributes a questionnaire that teachers can answer on a voluntary basis, and which is in fact returned by 90% of teachers submitting their evaluation materials. Based on the information provided by teachers in the questionnaire, we analyzed the scores from the separate instruments, as well as the combined total score in order to identify correlates of teacher's results. Table 3.19 summarizes the results of the ANOVA analyses using some key professional and personal antecedents of teachers. Considering the big number of cases included in the analyses (N=19,149), it is not surprising that almost all variables have significant effects on the teacher evaluations scores (the only non significant effect is teaching load on the supervisor score). However, the effects were not similar. The magnitude of the F values indicates that the most relevant factors were the subject matter, in-service training, sex and age. The duration of initial training and teaching had less important effects.

Table 3.19: ANOVA analyses of professional and personal teachers' antecedents

	Self Eval	Peer Eval	Supervisor Eval	Portfolio	Total Score
Sex	44.92**	10.79**	188.20**	228.97**	277.68**
Age	4.40**	4.06**	8.62**	41.74**	38.59**
Subject	123.62**	36.07**	7.43**	232.27**	200.50**
Duration of Initial training	4.97**	10.97**	13.06**	3.26*	12.92**
In-Service training	109.39**	69.94**	80.80**	30.28**	145.29**
Teaching load	3.25*	3.15**	1.36^{ns}	5.39**	6.29**

In order to identify the most important effects in teacher evaluation scores, Table 3.20 expresses each effect as standardized differences between the highest and lowest means compared[3]. As it can be observed, most of the effects are small. In the case of the self evaluation, the most relevant effect refers to the subject matter in which teachers work. Math teachers (closely followed by teachers from the other subject matters in the second half of primary education) evaluated themselves higher than general teachers by one third of a standard deviation. The other relevant effect is that of in-service training, which produced a smaller difference. This last effect is easy to interpret, because teachers who have spent at least a year in professional development have reasons to perceive their performance in a better light than teachers who have not received such a training. The differences in self-evaluation between general teachers (working in the first 4 years of primary schools) and their colleagues in grades 5^{th} to 8^{th} seems to reflect a status difference, which is not obvious, since most of these teachers received the same initial training, and

3 These standardized differences are the most typical effect size indicators. According to the convention proposed by Cohen, effects in the range of .2 to .3 are small, effects around .4 to .5 are moderate and effects higher than .8 are big.

their assignment to teach in the first or second half of primary education is not necessarily related to specialized training.

Table 3.20: Relevant effects for each instrument of teacher's evaluation.

	Standard deviation	**Highest effects observed**
Self evaluation	.554	Subject: .33 (math > general teachers) In service training: 0.17
Peer evaluation	.679	In service training: 0.14
Supervisor evaluation	.706	Sex: .24 (females>males) In service training: 0.17
Portfolio	.328	Subject: .71 (language > social sciences) Age: 0.44 (middle>older) Sex: 0.24 (females>males)
Total score	.301	Subject: .51 (language > social sciences) Age: 0.46 (middle>older) Sex: 0.23 (females>males) In service training: 0.22

The peer evaluation scores do not show strong relationships with any of the variables included in the analyses. In fact, the highest effect is a modest 14% of a standard deviation favoring teachers who have received in-service training lasting more than a year. In the case of supervisor evaluations (which typically combine the score of the school principal and the head of academic affairs in the schools), the largest difference relates to a non-professional antecedent of the teacher: their gender. Females are evaluated significantly better than males. Since this difference is similar in magnitude to the gender difference observed in the portfolio, it may not reflect a gender bias, but an actual performance difference.

The portfolio shows very strong differences related to the subject in which teachers work. Mathematics and Language teachers outscore Natural and Social Science teachers by more than half of a standard deviation (with general teachers in the middle). This difference does not match the self-evaluation difference between first and second half of primary education, and therefore, does not necessarily imply a status explanation. Initial and in-service training may be a more likely explanation, because due to the current focus on Mathematics and Language (a national program targeting those subjects in primary schools has been in place for almost a decade), teacher training programs may have adapted to those priorities, which may be producing a detrimental effect on social studies and science. It is important to consider that in Chile most teachers working in public primary schools do not have specialized training in the fields they teach. They receive a general initial training that covers all subjects. Professional practice and in-service training may be the only additional difference among teachers working in different subjects. The portfolio also shows important differences in the performance of teachers according to their age. Portfolio scores present an inverted U shape relationship with age, with middle-aged teachers having the highest scores. This is a usual pattern in different professions. In the case of Chile, the relatively high age average of public school teachers (M=49.8 in the sample of teachers included in this analysis) is troublesome, because older teachers are the ones presenting the lowest scores in the portfolio (even slightly lower than the youngest group of teachers). Gender and in-service training have similar effect sizes in the portfolio scores. Females or teachers who have received in service training lasting more than a year are about one fourth of a standard deviation above their counterparts. Gender differences do not have a clear explanation. As in most countries, female primary teachers clearly outnumber males, and the teaching profession is perceived as gender related. However, we do not have specific hypotheses for gender differences in performance. One possibility is that recruitment is differential for males and females, leading to a better stock of female teachers. Controlled studies about this issue are required in order to clarify this consistent performance difference, which also appears in the evaluations of school principals.

Finally, the effect sizes for the total score in the teacher evaluation program reflect the combined contribution of the different instruments. Therefore, no additional explanations are required for these effects.

Thus far we have analyzed the relationships between the scores on the teacher evaluation instruments and several personal and professional antecedents of teachers. However, the public communication of the results of this national assessment is not in terms of score points, but in the four performance categories that the program defines (ordered from lowest to highest: unsatisfactory, basic, competent and outstanding). During the first four years of the evaluation, a stable pattern of results has been observed. As can be seen in Figure 3.4, three to four percent of teachers are evaluated in the lowest category, and about one third of them is categorized as *basic*. Combined, these two categories represent performance levels that are below the national standards on which this evaluation is based (the Framework for Good Teaching). The largest proportion of teachers is categorized as *competent*, which is a category defined as complying with the standards, whereas a final eight percent are classified as *outstanding* (exceeding the standards).

Figure 3.5: Performance categories for teacher evaluation

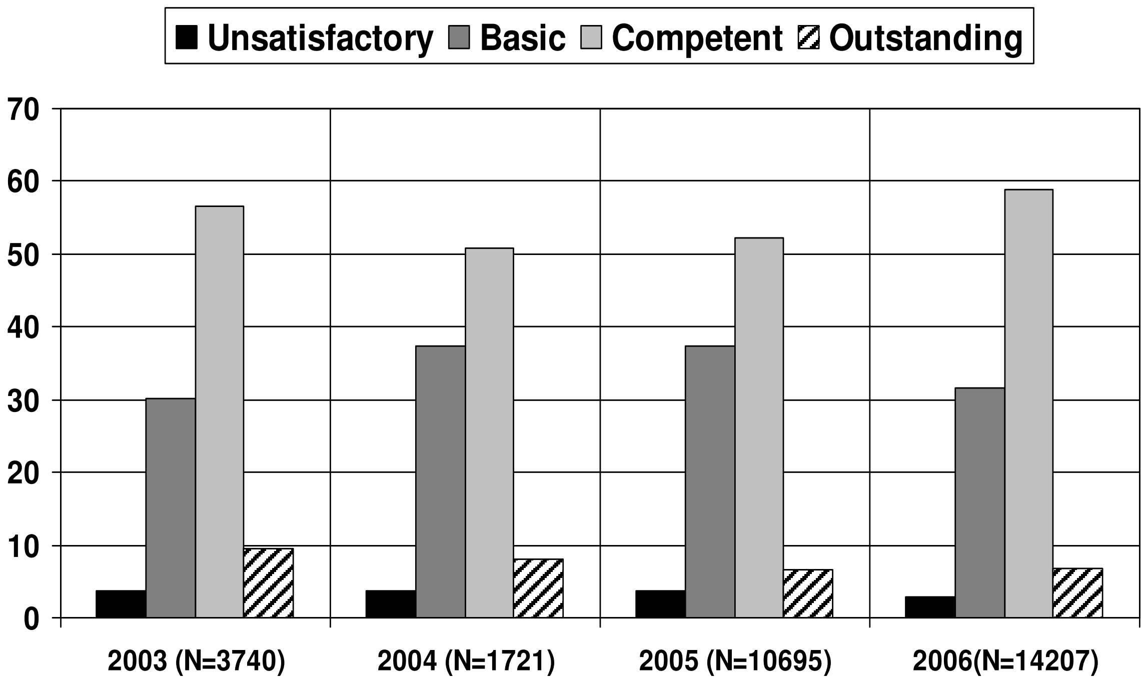
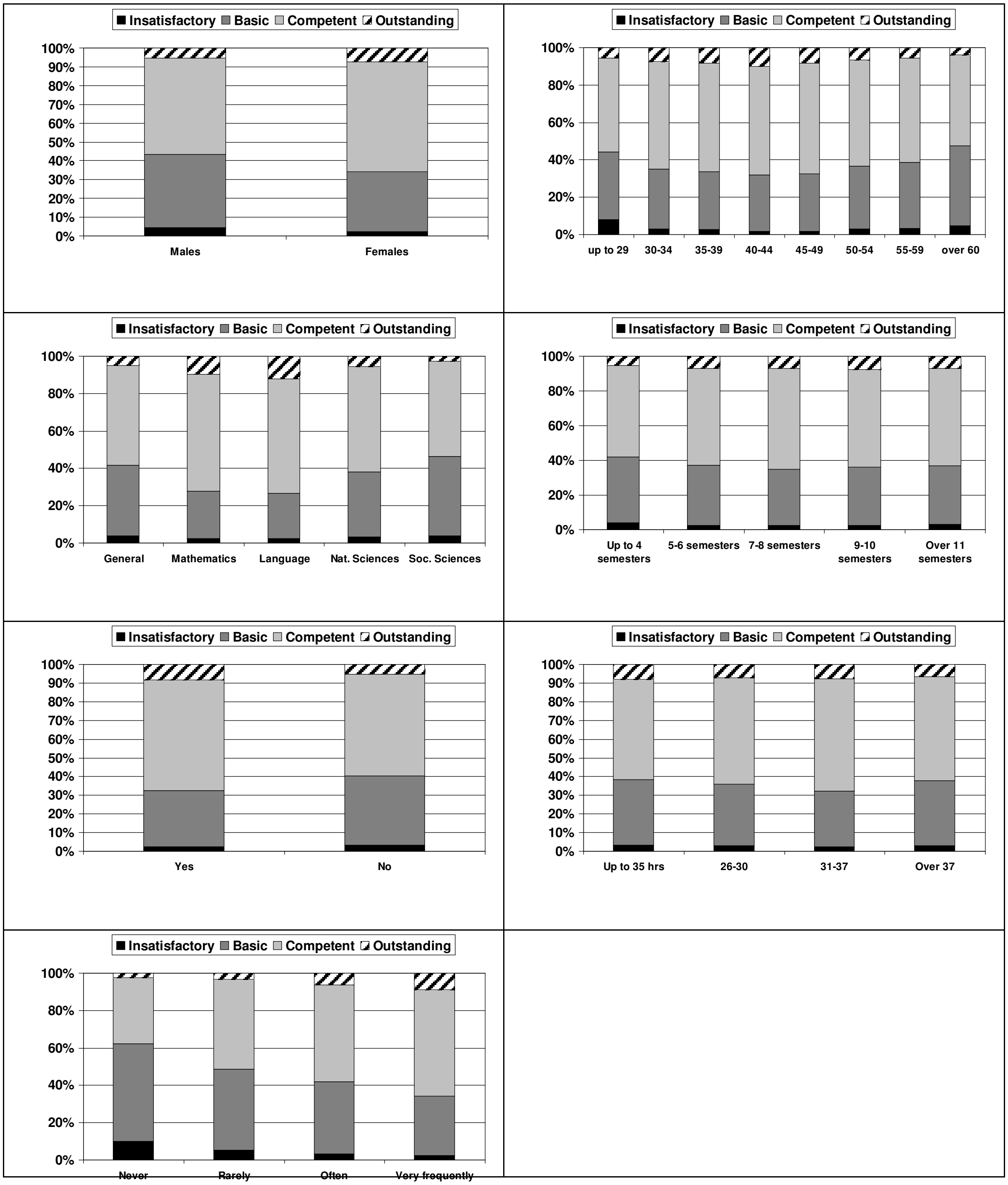


Figure 3.6 shows the relationships between the categorization of teachers in the four performance evaluations and the same variables previously analyzed. In statistical terms this analysis does not add additional information to the results summarized above, but it clarifies the specific pattern of the differences, and it also presents results in the same scale that they are communicated to teachers each year. All the relationships represented in Figure 3.6 were statistically significant using the chi-square test.

Figure 3.6 Relationship between the categories of teacher evaluation and gender (panel a), age (panel b), subject matter (panel c), duration of initial training (panel d), in-service training lasting more than a year (panel e), teaching load (panel f) and the use of computers (panel g)



3. 6 Conclusions: Individual, School and Teacher effects on standardized test performance in Chile

The previous analyses have shown several significant effects on student performance in the 4th grade Language and Math SIMCE test. Of these, several replicate findings of previous studies. Specifically, the relevance of the socioeconomic factors in determining children's results in these tests in Chile, which has been found by many other studies, is confirmed in these analyses, with the additional information that school aggregates of socioeconomic composition also have an effect on the student's performance. That is, that children of low socioeconomic status perform even worse in schools where there is a homogeneous composition of low-SES students, than they would if they were integrated into higher-SES schools. Also, using data from other national standardized tests (other SIMCE tests and the PSU tests), we were able to observe that these individual and group-SES effects are consistent across grades, years and tests.

Two novel results emerge from these analyses. In the first place, we found that schools whose parents claim that information on school test results is known and used, tend to obtain higher scores in language and math 4th grade SIMCE tests. And second, we found a significant effect of the school's average teacher evaluation scores, which is not easily explained away by possible selection bias in the way schools select their teachers. This effect of teacher evaluation scores is consistent with very recent results by other researchers. Eisenberg (2008) studied both the distribution of teacher scores across different kinds of schools in Chile and the effects of teacher evaluation scores on students' achievement in SIMCE tests. With regards to the distribution of teachers, Eisenberg found that the proportion of high-performing teachers is higher in schools with higher SES and with higher student achievement, and also in municipalities without accessibility problems and with traditional forms of educational administration. This is in slight contradiction with our claim that school variables do not influence teacher score, but the types of evidence are different, since we base our claim on low between-school variance of teacher scores. More interestingly, with regards to the relation between teacher evaluation scores and student achievement, Eisenberg's results are consistent with our own, since she also found a positive effect of teacher scores on achievement, although using the aggregated teacher score instead of each instrument separately, and matching teachers and students at the classroom, not the school level (therefore she used only the small subsample of teachers who could be matched directly to the 4th grade students they had taught that year. This finding at the classroom level supports the interpretation of our effects as plausibly causal, instead of representing possible teacher selection biases of the school.

4. Quality of Education and Quality of Life in Chile4

4.1. Introduction

Globalization of markets and the transition to an information economy are dramatically changing the nature of work. In this context, knowing how to read and write is not enough to ensure adequate work performance; it is necessary to do so with ever increasing capacities (OECD, 1997). The IALS Project (International Adult Literacy Survey) is an OECD initiative5, whose purpose is to evaluate the literacy abilities of the population over 15 years of age.

The term literacy is used in this context not only to refer to the ability to read and write but rather to refer to a particular type of basic skill: the ability to understand and use written information in the context of home, community and work duties. The concept can be referred to as "functional literacy".

Functional literacy relates to the quality of the insertion a person may have in the social and economic life of a country. Clearly, deficiencies in information comprehension and processing lead to low productivity levels and a deficient economic insertion. Equally,

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5 The development and administration of the survey is the responsibility of Statistics Canada and the Educational Testing Service of the United States.

those individuals can expect to have disadvantages in their participation as political citizens and social actors.

This study examines the relations between functional literacy, thought as a better measure of quality of education, and quality of life in Chile. Relations between education and quality of life indicators have usually relied on measures of the quantity of education, such as years of schooling or degree obtained. Studies that examine connections with quality of education (measured through attainment on achievement tests) are rare and have only recently appeared. In Chile, such an endeavor presents many challenges, since existing data on tests such as SIMCE, PISA or TIMSS does not lend itself to be linked to any existing data on quality of life at the individual level, since the latter are usually collected at the household level (for example, through the CASEN survey).

An additional challenge is that most existing achievement-test data in Chile are not available for individuals old enough to have entered the labor market yet, or at least not in sufficient proportions. There is however, one source of Chilean data that offers at the same time cognitive skills scores and data on occupation and income on adults. This is the IALS administered in Chile in 1998, which measures three dimensions of literacy skills in adults in the labor force 15 through 65, and also collects other data such as labor participation, job qualifications, income, years of education, years of experience, years of training and parents' education, among others.

The goal of this chapter is to use IALS data in order to examine contributions of cognitive skills to different indicators of quality of life. Specifically, we use the IALS score to predict three aspects of quality of life: occupational status (measured by labor participation and job hierarchy), earnings and poverty.

This chapter is structured around four sections, apart from this introduction. The second section describes the IALS survey together with its main findings. The third section analyzes the determination of the literacy skills on the base of a model of accumulation of the same through schooling and the use of the skills in work. The fourth section analyzes the impact of literacy skills on occupational status, earnings and poverty. The fifth section concludes.

4.2. The International Adult Literacy Survey (IALS)

The IALS was administered in 1998 to a nationally representative sample of 3583 Chileans aged 15 to 65 (labor force).

The survey treats literacy as a continuous variable instead of the traditional dichotomous concept. The concept is related to the literacy abilities which individuals require to operate in society. The basic skills are presented in three dimensions:

- *Prose*: the necessary knowledge and skills for understanding and using information contained in texts such as editorials, news stories and literary texts.
- *Document*: the basic knowledge and skills necessary in order to find and use information contained in documents such as charts, maps, graphics, indexes, etc.

- *Quantitative*: the basic knowledge and skills necessary to carry out arithmetic calculations in printed text, such as the calculations that may be necessary to fill in bank deposit slips, estimate time using timetables, etc.

The IALS uses the *Item-Response Theory* as much to evaluate the difficulty level of the questions as to give scores to the respondents.6 They are scored separately in the different areas on a range between 0 (lowest ability) and 500 (highest ability), classified into five levels.

The evaluation instruments used in the IALS are common to all participating countries, so it is necessary to be careful in the adaptation of the original English version to the other languages.

In the survey, each respondent must first answer a background questionnaire that gathers relevant socio-demographic data. Subsequently, a central booklet of tasks is given with six simple questions to complete associated with five assignments. If the respondent fails to correctly answer at least two of these questions, the interview is terminated. Otherwise, if more than two questions are correctly answered, a main booklet of tasks is given. There is no time limit in completing the test, so that the person may have all the time necessary to show their abilities.

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6 See T.S. Murray, I.S.Kirsch y L.Jenkings (eds.), *Adult Literacy in OECD Countries: Technical Report on the First International Adult Literacy Survey, 1997.*

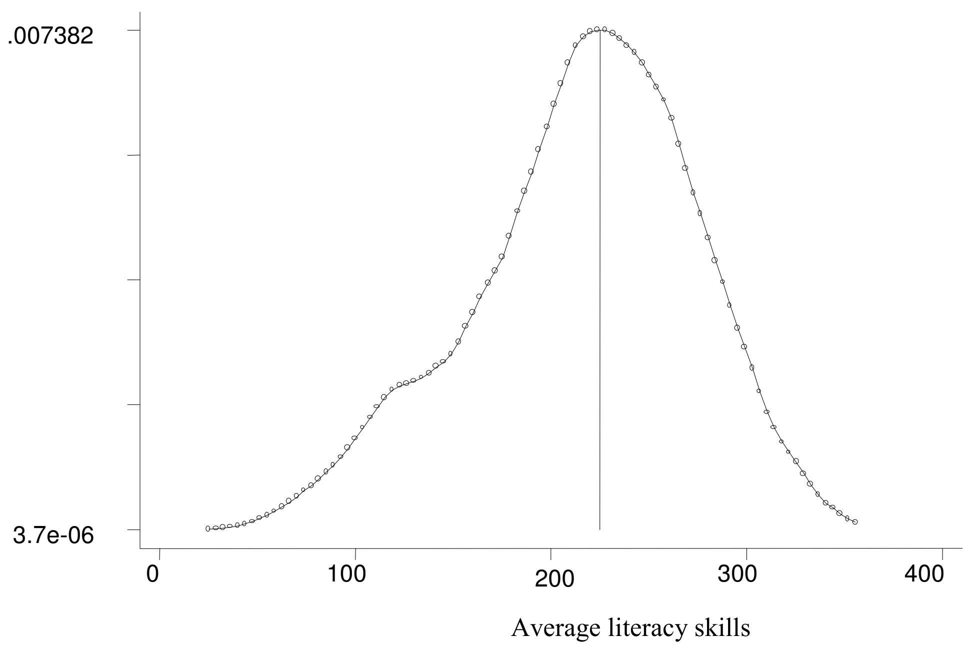
First time round, the survey was carried out in 12 OECD countries. This was carried out between 1994 and 1996 (OECD, 1995 and OECD, 1997). The second version was carried out in 1998 and incorporated 10 other countries, including Chile.

In Chile, the survey was carried out in May and June 1998, and its implementation was the responsibility of the Department of Economics of the University of Chile. The survey has to satisfy demanding standards set by the ETS and Statistics Canada that ensure the statistical reliability and comparability of the information gathered among the participating countries.

4.2.1 IALS results

Table 4.1 presents the scores associated with different percentiles of the distribution for the prose, document and quantitative domains. Figure 4.1 shows the distribution of the results, considering the average of the three domains.

Figure 4.1: Distribution of literacy skills, average three domains



The mean score for the total population fluctuated between 222 in prose, 219 in document and 210 in the quantitative section. The median (percentile 50) presents similar levels, given that there is certain symmetry in the score distribution.

The official statistics in Chile show that only 4.6 per cent of the population over 15 years of age declare themselves unable to read or write. However, over 50 per cent of the population falls into level one of the IALS survey (below 225 points), indicating a very low level of written text comprehension.

Table 4.1

Chile: Distribution of literacy skills

	Prose	Document	Quantitative
5th	124.5	121.2	85.0
10th	145.6	142.5	111.5
25th	187.1	188.2	166.9
50th	225.9	223.9	215.7
75th	258.9	256.6	257.6
90th	286.1	283.3	292.5
95th	301.2	299.0	312.5
Average	221.5	219.4	209.8
Standard Deviation	53.4	53.6	67.7

Source: Authors' calculations based on IALS survey

Table 4.2 shows that the average level of literacy skills depends on labor market participation.7 People who participate in the labor market show a higher average level of skills relative to those who do not participate.8 This could indicate that those with higher earning potential have a higher probability of participation; on the other hand, it could indicate that using these skills in working activity helps develop those skills even further.

7 Henceforth the average results from the three components will be used. This is due to the high correlation coefficients that were found: 0.925 between prose and document; 0.924 between prose and quantitative; 0.945 between document and quantitative.

8 Throughout the text, labor market participation includes those who have had some job in the last 12 months.

Table 4.2: Basic Skills and Labor Market Participation

People between 15 and 65 years old (non-students)

	Men			Women		
	Literacy skills level		Participation rate	Literacy skills level		Participation rate
Age	Participation	Non Participation		Participation	Non Participation	
15-24	228.5	198.1	90.4	230.8	208.6	54.7
25-34	225.9	171.1	97.6	231.8	213.9	56.7
35-44	213.5	127.6	96.7	222.0	207.6	53.3
45-54	202.9	160.6	92.5	212.7	186.2	45.1
55-65	192.9	197.9	79.7	211.1	169.0	32.5
15-65	215.3	179.2	93.2	224.2	198.1	50.2

Source: Authors' calculations based on IALS survey

4.3. Determinants of Basic Skills

Literacy skills can be categorized as cognitive skills, and as such continue developing throughout ones life via a dynamic interaction between abilities and learning (Heckman, 1999). People with greater abilities learn more, while learning generates more abilities. We can identify three stages in this process: the first is pre-school education which depends largely on the family context; the second is the formal education stage; and the third is the work context learning which significantly contributes to the development of these abilities.

Notwithstanding, the most effective inputs occur in the earliest learning and ability development stages.

The relation between functional literacy and job opportunities has been the subject of several recent studies basing themselves on surveys that measure the literacy skills of the population. The OECD and Statistics Canada study presents a comparative analysis between countries for the results from the second International Adult Literacy Test which was carried out in 1998 (OECD, 2000). The study recognizes the interdependence between job opportunities and functional literacy, though there is no clear view as to how these effects work.

For most of the countries (17 out of a total of 20) the schooling years are recognized as the principal determinant of literacy skills, even though great differences can be observed among people with the same education level among different countries. People ages have an inverse relation with functional literacy, but the authors have not offered an interpretation for this result. Labor market participation, occupation type, the formal adult education and informal work based learning, show a statistical association with literacy skills in most of the countries. Moreover, it shows that the probability of unemployment is inversely related to the functional literacy level; while salaries increase together with the skills level, after controlling for other variables in an amplified Mincer equation.

Pryor and Schalaffer (1999) established that schooling, gender, age and education of the mother, account for 46 per cent of the variance of the results of the National Adult Literacy

Test in the United States, with the years of education as the most important of those variables. The authors interpret this relation as a reduced form, since there is no theory to explain functional literacy.

There is no well developed theory for explaining the development of literacy skills. However, the previously cited empirical evidence identifies the learning obtained at home and in school as determinant, as well as the subsequent practice of those skills.

Thus, it is possible to postulate that the literacy skills rest on the notion of stock or accumulation over the course of time. The level of literacy skills that a person possesses in the present period (Y_t) depends on two types of processes. In the first place lays the development of these skills through education, as well as in the parental home. Secondly, once the formal education is finished, literacy skills can increase or decrease depending on the degree of use of those skills in their day-to-day activities.

Thus, the skill level of a person can be expressed as:

$$Y_t \quad = \quad \int_{to}^{t'} s_v(z_o)\,dv \quad + \quad \int_{t'}^{t} q_v(z_1)\,dv \qquad (1)$$

The first integral corresponds to the accumulation of skills done in schooling system, which occurs in the time interval $v = [t_0,\ t']$. The s function (.) denotes the transformation of schooling into skills, which, it is supposed to depend on a vector of variables z_0 which includes the quality of the education, the educational atmosphere at home and person's abilities, among others.

The second integral denotes the accumulation of skills after schooling is finished, corresponding to the time interval between the year of leaving school and the present period: $v = [t', t]$. In this case, the accumulation of skills occurs through function q(.), which depends on a vector z_1 that includes variables related to the practice of these skills in work or at home (habit of reading, numerical calculations, etc).9 The previous expression should be interpreted as a reduced form. A more complete model should consider the possibility that the years of schooling as well as the work-based practice depend on cognitive abilities, which are in turn developed with education and work based practice.

Without practicing these skills deterioration over time can be expected, that is:

$$q_v(0) \leq 0 \qquad (2)$$

In the particular case that the functions s(.) and q(.) be invariant over time; that is $s_v(.)= s(.)$; $q_v(.)=q(.)$, the integral that denotes the accumulation of skills can be expressed as:

$$Y_i = S(z_0) + Q(z_1) \qquad (3)$$

9 The assumption that schooling and the subsequent use of the skills occurs in consecutive time periods is only for analytical presentation convenience.

The skills depend on the years of schooling (S) and on the subsequent years after leaving formal education (Q), denominated here forth as "potential work experience". The effect of these cycles on the accumulation of skills depends on the "*z*" factors cited above.

4.3.1 Empirical Evidence

The relation between literacy skills, schooling and age is examined in Table 4.3. There it is shown the average level of literacy skills for education-age groups, excluding current students. It should be noted that working with education-age groups provides similar information to considering the potential experience variable instead of the age variable.10

Table 4.3: Mean literacy skill level

Men who participate in the labor market

Age groups	Years of schooling					
	0-4	5-8	9-11	12	13 and over	Total
15-24	---	198.3	235.1	240.5	273.8	228.5
25-34	139.8	180.0	209.6	235.9	287.0	225.9
35-44	159.4	174.0	222.6	235.1	264.4	213.5
45-54	140.7	196.8	216.9	235.7	250.8	202.9
55-65	144.6	185.0	246.0	234.0	269.3	192.9
Total	147.7	185.0	220.6	236.3	271.3	215.3

Source: Authors' calculations based on IALS survey

10 In Table 3 there is not enough data available for the younger age group with lower education. See Table A-1 of the Annex.

The data shows a strong association between literacy skills and years of schooling, which goes for the different cohorts. This is in line with the empirical evidence from other countries that identifies education as the most important variable in determining literacy skills.11

The data also shows a marked negative correlation between the literacy skills and the age of the people (Table 4.3, last column). This relation can be due to cohort or life cycle effects. To separate both types of variables it would be necessary to have more observations over time. However, the available evidence points to the predominance of effects linked to the working life cycle of people.

In this regard, consider that the cohort effect refers to factors that, affecting differently each cohort, relate to the development of literacy skills. Examples of this are the quality of the educational system and the information tools that the cohort possesses when young (written media, television, internet). On the other hand, the factors related to the life cycle relate to the use made by people of those skills throughout their work experience.

Table 4.3 shows that the relation between skills and age is significantly modified when schooling is taken into account. Thus, these skills drop with age only in the lower education levels, while the skill levels remain relatively constant at all ages for other education levels.

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11 OECD and Statistic Canada *: Literacy in the Information Age. Final Report of the International Adult Literacy Survey*, Paris, 2000.

The different temporal trajectories shown by skills when considering years of schooling would reflect the greater importance of life cycle factors, even when one cannot exclude the possibility that cohort variables interact with variables related to years of schooling attained (for example, people with higher education have greater access to information means, which in turn change through generations).

Notwithstanding the aforementioned, the evidence on the use of the skills in work reinforces the effect linked to life cycles. To see this, consider that the IALS contains information on the use of literacy skills in the job, measured as frequency of "use of reading and information in work" and "practice of writing in work". Working from this information, a variable is created that represents the degree of use of literacy practices in work, which fluctuates between 0 and 24 points, with an average value of 5.80 and a standard deviation of 6.13.

Table 4.4 shows that the intensity of the use literacy skills in work, as well as its evolution over time, are closely related to the level of schooling of the person, a variable that is, in turn a proxy of the level of skills that a person has when commencing their work cycle.

Table 4.4: Index of the use of literacy skills in work

Men who participate in the labor market

Age groups	Years of schooling					
	0-4	5-8	9-11	12	13 and over	Total
15-24	---	1.82	4.74	7.57	10.21	5.24
25-34	0.49	2.54	5.09	7.62	11.22	6.47
35-44	0.63	2.31	5.09	8.89	10.55	5.84
45-54	0.69	2.73	5.89	6.11	13.45	5.59
55-65	0.60	4.03	7.76	8.03	13.71	4.87
Total	0.62	2.55	5.28	7.94	11.61	5.80

Source: Authors’ calculations based on IALS survey

Thus, workers with low schooling demonstrate a minimal use of literacy skills in work, which would help explain the fall seen in their skills over time. As such, we would be looking at people who start working with low literacy levels and enter jobs that do not require the use of those skills, thus generating a situation that would lead to reduced literacy skills over time.

As schooling increases, the rate of use of literacy skills in work increases. Thus, the higher the initial skill level, the higher the probability of entering jobs that require the use of those skills. More interestingly, the use of these skills in work actually increases over time for these people, suggesting the existence of a dynamic relationship between skills level and the use of those skills in work.

4.3.2 Regression Analysis

The evidence presented is clear in order to outline the relation between literacy skill level, schooling, and the practice of those skills in work. Here we present a multivariate analysis to confirm if the previous results are robust to the inclusion of other controls related to literacy skills.

Table 4.5 presents the results obtained for regressions that incorporate the different factors associated with the dependent variable: the literacy skills level of the men who are participating in the labor force. These include schooling, quality of education (according to type of school attended) and educational level of the mother, a variable that shows the resources present in the parental home. To capture the effects of the work cycle on the use of the skills, the potential work experience variable is included, the interaction between this variable and the index of the use of the skills, as well as the interaction between the previous variables and schooling level.

A potential problem in the regression is that the variable "use of the skills" is endogenous, given that the people whose work demands literacy skills could have been chosen for those jobs precisely because they had a higher initial skills level. Nevertheless, here we postulate that the variable is predetermined given that the past accumulation of skills is important, measured via the interaction between the potential experience and the use of those skills. The necessary assumption here is that, given that there are no panel data available, the use of the skills over time has some type of continuity. The data presented in Table 4.4 is consistent with this assumption.

The results of the regression identify years of schooling as the principal skills determinant. The marginal effect of the variable depends on the specification used, in a range that varies between 5.9 and 9.4 additional points in the literacy skills level for each additional year of schooling. If the specification (4) is considered, which the preferred specification is, every additional school year would increase the skill level in 6.7 points (equivalent to 11.4% of the standard deviation of the variable).

Table 4.5: Literacy Skills Determinants

Men who participate in labor market (OLS, robust, test-t in parenthesis)

Dep. variable: Literacy skills level	(1)	(2)	(3)	(4)	(5)	(6)
Years of schooling	9.376	7.978	6.866	6.665	6.463	5.888
	(20.18)	(9.76)	(8.64)	(8.35)	(8.14)	(7.09)
(Potential) work experience	-1.017	-1.648	-2.225	-2.473	-2.396	-2.350
	(2.72)	(3.11)	(4.27)	(4.64)	(4.51)	(3.85)
Work experience^2	0.016	0.024	0.030	0.033	0.032	0.028
	(2.43)	(2.79)	(3.54)	(3.84)	(3.67)	(2.83)
Work experience*D1		0.491	0.617	0.929	0.943	1.104
		(1.01)	(1.31)	(1.88)	(1.91)	(1.97)
Work experience^2*D1		0.002	-0.006	-0.008	-0.008	-0.005
		(0.13)	(0.51)	(0.70)	(0.71)	(0.39)
Work experience*D2		2.039	2.129	1.989	2.068	2.671
		(2.50)	(2.82)	(2.41)	(2.57)	(3.10)
Work experience^2*D2		-0.074	-0.086	-0.087	-0.087	-0.100
		(2.43)	(3.14)	(3.22)	(3.24)	(3.27)
Work experience*Use of skills in work			0.072	0.125	0.125	0.148
			(5.06)	(4.82)	(4.89)	(4.73)
Work experience*Use of skills in work*D1				-0.072	-0.074	-0.109
				(2.35)	(2.47)	(3.07)
Work experience*Use of skills in work*D2				0.028	0.022	-0.002
				(0.67)	(0.52)	(0.04)
Private schooling					10.045	8.625
					(1.43)	(1.14)
Voucher schooling					4.245	5.682
					(1.01)	(1.23)
Mother's educational level						1.160
						(2.16)
Constant	135.868	150.755	163.576	166.341	166.061	163.624
	(18.12)	(13.53)	(15.13)	(15.33)	(15.49)	(13.62)
Adjusted R2	0.48	0.49	0.51	0.51	0.51	0.52
Observations	1301	1301	1301	1301	1301	1099

Note: D1: dummy equals 1 if individual has secondary education
D2: dummy equals 1 if individual has higher education

The specification (4) does not include the variables related to the formation of skills while at school, beyond simply the years of schooling. In this regard, it should be noted that the variables that distinguish between types of educational establishment give coefficients that are not significant (specification (5)). On the other hand, including the mother's educational level gives a positive and significant variable on the skills level (specification (6)). The problem in this case is that a relatively high percentage of observations without data for the variable exist (15.5%), which are distributed in a non random way by age and schooling.

The relation between schooling and skills level is linear (see figures 4.2 and 4.3). 12 This is an important result given that in the Chilean case the relation between schooling and earnings is markedly convex, due to the high rates of return of higher education with respect to primary and secondary education. There is also recognition for those finishing secondary school in the labor market, connected to a credential effect if that attainment is a sign of attributes sought by employers but which are difficult to observe directly in applicants (responsibility, discipline, etc). Nevertheless, the monotonous relation identified between years of schooling and literacy skills level vindicates to some extent the value of each additional year of education.

[8] More flexible functional forms for the relation between schooling and skills were also proved.

Figure 4.2: Literacy skills and years of schooling

(Men in the labor force, non conditional effect)

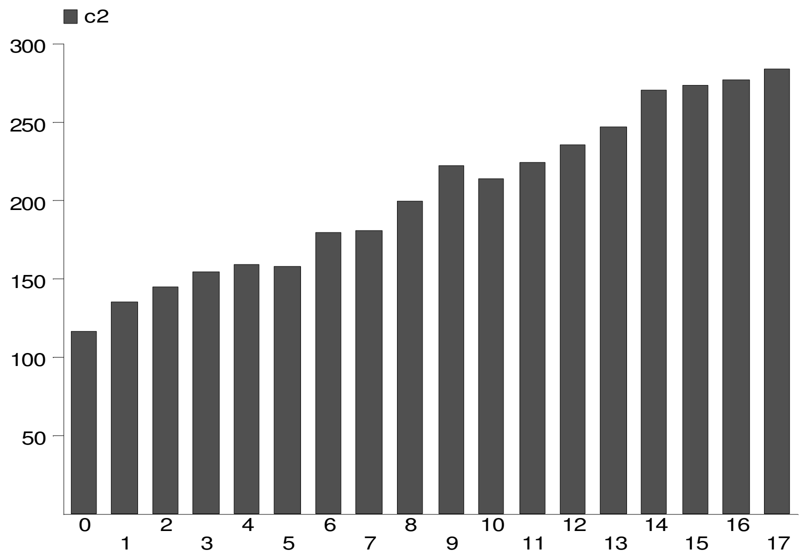
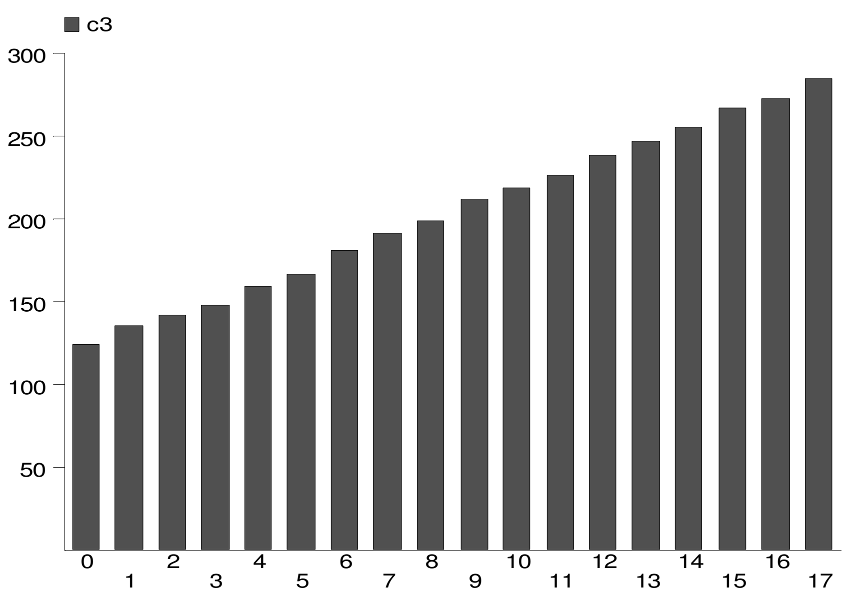


Figure 4-3: Literacy skills and years of schooling

(Men in the labor force, conditional effect on regression 4, table 4.5)



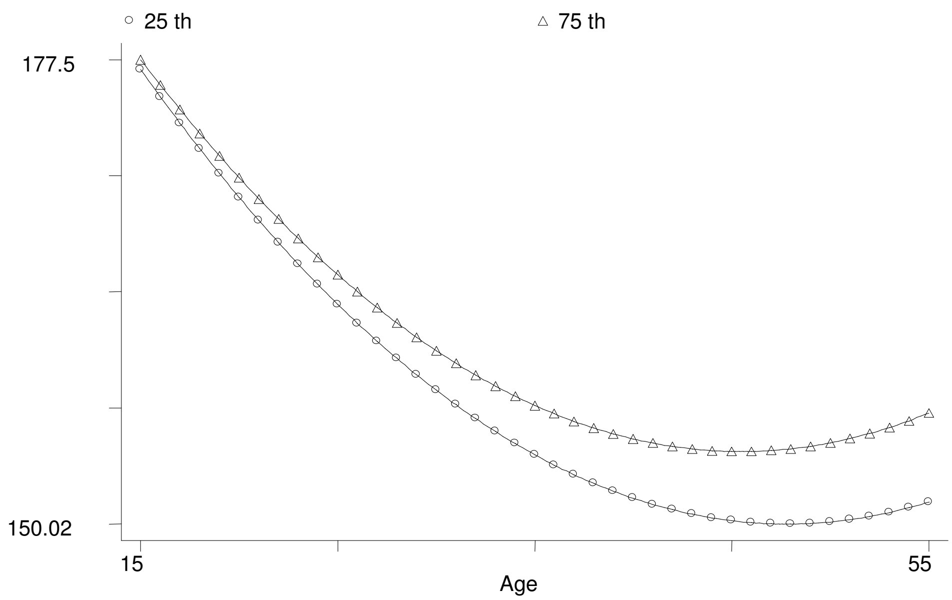
The relation between years of schooling and skills level could be contaminated by the omission of variables, such as unobserved genetic abilities. However, the graphs do not present any evident signals of discrete changes in those years of schooling (8, 12) which represent the final stages of education for lower ability students (conditional on socio-economic variables). That should occur to mediate important effects of unobserved abilities in the relation between schooling and basic skills.

A second important result is the dynamic presented by literacy skills levels after leaving formal education. For workers with primary and secondary education, the skills would tend to deteriorate over time in a concave relation (deteriorates at slower rates). On the other hand, workers with higher education show a tendency of higher skills levels over the course of the work cycle. These relations are modified according to the use of those skills in work.

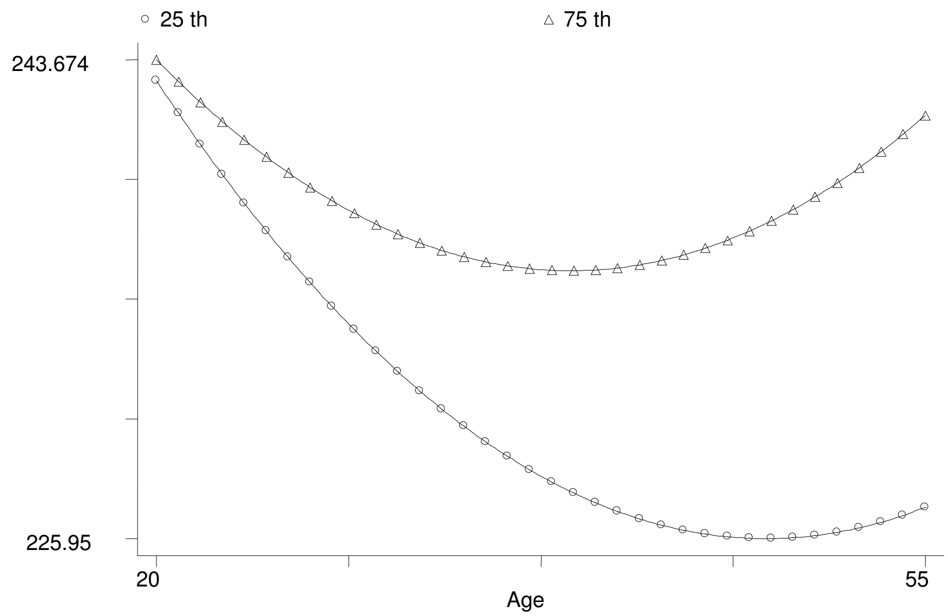
The temporal dynamic of the basic skills is illustrated in Figure 4.4. This shows the predicted trajectory of the basic skills in the period following formal education. To that effect, the coefficients estimated in the literacy skills regression are used (Table 4.5, fourth column). Different cases are shown, by years of schooling (4, 12 and 17 years) and by level of use of skills in work, considering people located in the 25 and 75 percentile of the distribution of that variable.

Figure 4.4: Literacy skills over working cycle
(Percentile 25 and 75, in use of skills in work distribution)

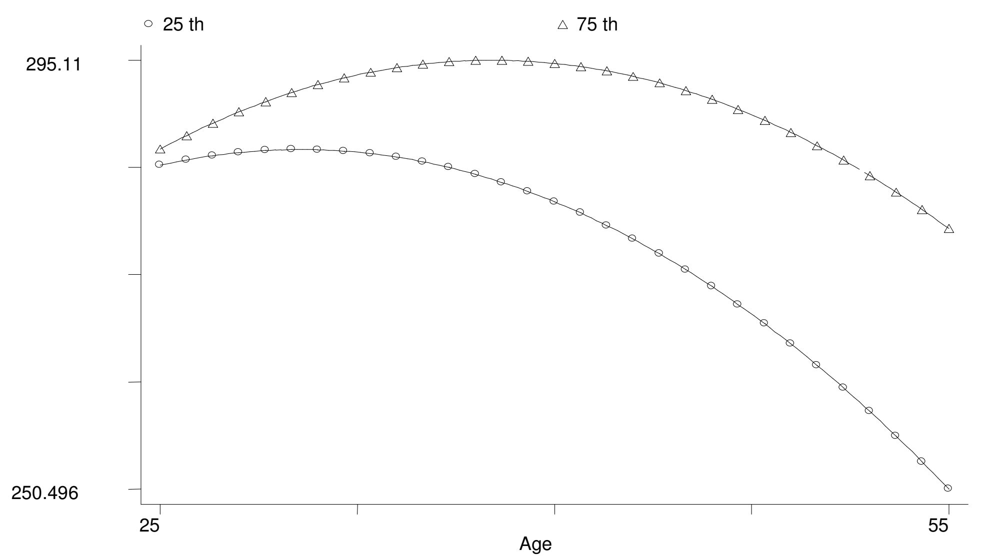
<u>(i) 4 years of schooling</u>



(ii) 12 years of schooling



(iii) 17 years of schooling



For people with four years of schooling, there is a significant drop in these skills over the course of their working cycle, from an already low initial level. Moreover, the degree of use of these skills in work has a lower effect on the trajectory of those skills over time. This shows that this group presents few differences in the use of the skills. These are people who do not typically enter jobs where these skills have to be used, as a consequence of the low levels that they have to begin with.

On the other hand, there are significant differences in the time trajectories of these skills for people with twelve years of schooling depending on the extent of their use in work. As such, a person in the percentile 25 in the use of these skills experiences a reduction of around 25 points in the skills between 20 and 55 years of age, while a person in the percentile 75 practically sees no deterioration in these skills levels over the course of their working cycle.

A similar situation occurs in the case of people with higher education. Those in the percentile 25 of the use of the skills in work experience deterioration in skills levels throughout their working cycle. On the other hand, the greater use of these skills (percentile 75) is associated with the preservation of these over time.

In general terms, the regression analysis confirms the conclusions derived from the previous analysis. The skills level is linked to the schooling level as well as to the use of these skills in work; this variable in turn depends on the initial skill level. The empirical evidence is consistent with a dynamic relation between the development and the use of these skills.

4.4. Literacy Skills and Quality of Life

4.4.1 Results for Occupational Positions

In this section we use the IALS score to predict two aspects of occupational position: labor participation and job hierarchy. Individuals' participation is defined as the willingness to work (employed and unemployed people) with respect to labor force. Job hierarchy is defined as the probability that the person occupied a position of supervision responsibilities in his or her job.

The IALS data have already been previously and partially analyzed by Bravo & Contreras (2001). In comparison with this study, we will extend the analysis doing a deep examination of the correlation between labor outcomes and IALS test score controlling for other socio economic characteristics including age, gender, years of education, head of household status, non-labor income, marital status, job characteristics, training and geographic factors. We also differentiate the effects of the average IALS test score and its components (Prose, Documents and Quantitative). Finally, given that the functional form between quality of life and test scores is unknown, both parametric and non parametric estimates will be used to examine such relationship.

Table 4.6 presents probit model estimates for the probability of participate in labor market. We use socio demographic control variables such as gender, age, marital status, head of household, years of schooling, non labor income, training courses, and literacy skills. In addition, we use geographic characteristics such as rurality.

We found that years of schooling affect positively the probability of participation, which is consistent with the hypotheses that more prepared individuals, will be more willing to participate in labor force because they are more productive and will earn more. We also found that labor participation increases with age but at decreasing rates. In addition, men and heads of household are more prone to participate, whereas a higher non labor income is related to lower participation.

These results are consistent with labor economic theory in which cost-benefit analysis between market and reserve wages is relevant to determine labor participation. In this framework, reserve wage is determined by factors such as gender, age and non labor income.

Higher average skills are related with higher participation probability (specification 5). One extra point in the IALS test is associated with a 35 percentage point increase in participation probability, once one control for schooling, age, gender, marital status and the other factors considered in the regressions.

Table 4.6: Basic Skills and Labor Market Participation – Regression analysis

People between 15 and 65 years old (non-students)

(Marginal probabilities / robust test z are in brackets)

Variable	(1)	(2)	(3)	(4)	(5)
Average Score:					0.3494
					[2.52]
Prose	-0.0027	0.0000	0.0002	0.0002	
	[4.85]	[0.05]	[0.74]	[0.65]	
Document	0.0010	0.0016	0.0011	0.0011	
	[1.45]	[2.44]	[3.07]	[3.13]	
Quantitative	0.0017	-0.0007	-0.0007	-0.0008	
	[3.02]	[1.37]	[2.47]	[2.63]	
Individual characteristics					
Years of Schooling	0.0177	0.1870	0.7171	0.0056	0.0049
	[5.00]	[5.06]	[3.39]	[2.61]	[2.32]
Age	0.0202	0.0267	0.0139	0.0135	0.0141
	[3.76]	[4.94]	[4.02]	[4.00]	[4.19]
Age^2	-0.0003	-0.0004	-0.0002	-0.0002	-0.0002
	[4.29]	[5.54]	[5.00]	[5.03]	[5.33]
Male = 1		0.3742	0.1805	0.1831	0.1721
		[15.75]	[9.92]	[9.93]	[9.47]
Head of household=1		0.1642	0.0305	0.0305	0.0314
		[6.54]	[2.11]	[2.18]	[2.19]
Single =1		0.0828	0.0100	0.0074	0.0115
		[3.68]	[0.76]	[0.58]	[0.89]
Non-labor income			-0.00001	-0.00001	-0.00001
			[2.29]	[2.23]	[2.30]
Some trainning=1				0.0371	0.0364
				[2.47]	[2.40]
Geographic characteristics					
Rural zone = 1				-0.0285	-0.0265
				[2.03]	[1.91]
Pseudo R2	0.07	0.30	0.29	0.29	0.28
Chi2 test	174.57	552.63	300.72	296.83	275.71
Observations	3206	3206	2242	2242	2242

Notes: Dependent variable is a dummy equal 1 if individual participated in labor market and 0 if not.
Labor market participation includes those who have had some job in the last 12 months.
Some trainnig is a dummy variable equal 1 if individual has receive some educational or training course in the last 12 months.

Different type of skills, however, has different effects on labor participation (specifications 1 to 4). In particular, whereas document skills positively affect labor participation probability, the score in prose not seem be important. On the other hand, quantitative skills affect negatively the participation probability.

Figure 4.5 shows the results of semi-parametric estimation of the relationship between average skills and labor participation13. We note that the relation is non linear, and particularly cubic. Higher skills are associated with higher participation probability for intermediate levels of basic skills, but the relation is weaker for lowest and highest levels of basic skills.

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13 We follows Robinson's (1988) semiparametric approach that consists in the following formulation: $E[Y / X, S] = \beta' X + \phi(S)$. Where the function $\phi(S)$ is estimated using nonparametric techniques such as kernels, S stands for skills and X vector contains the other controls.

Figure 4.5: Non-linear Relation between Labor Participation and Literacy Skills

People between 15 and 65 years old (non-students)

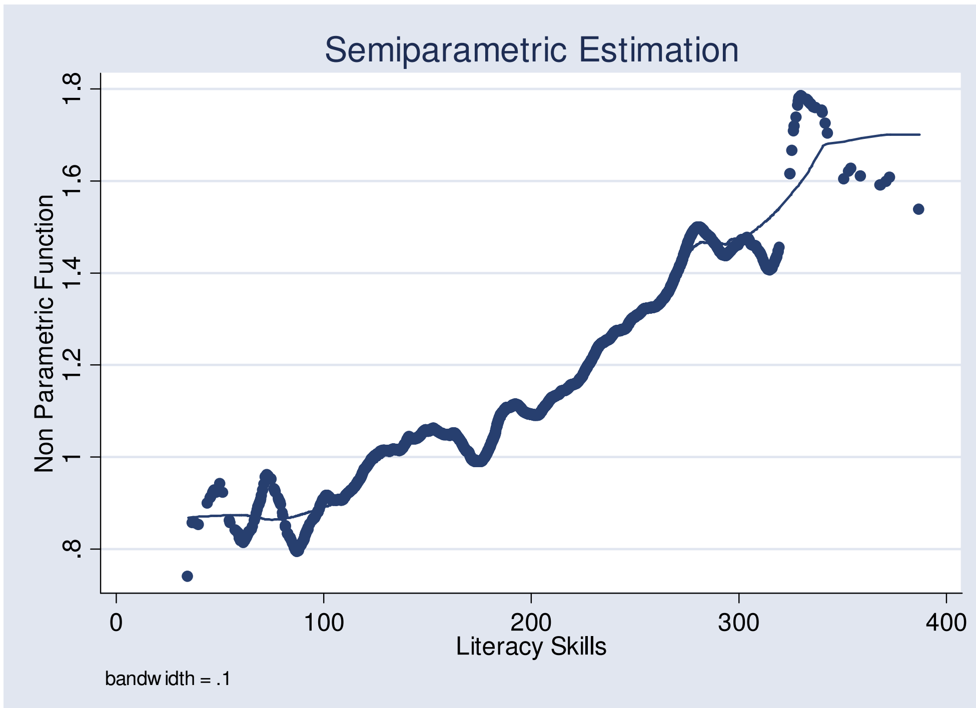


Table 4.7 presents probit model results for the probability that the person occupied a position of responsibility in her o his job, that is, we consider workers with subordinate people to charge. Capital human factors such as schooling and experience show a positive effect on the probability of occupied responsibility positions. We do not find gender differentiation in the access to responsibility positions, whereas labor conditions, such as full time jobs, and upper relative position in income distribution are positively associated with responsibility positions.

Finally, controlling by all previously mentioned factors, average skills has a positive, although little, effect on the probability to access to responsibility positions. Ten extra points in the IALS test is associated with a 0.7 percentage point increase in this probability.

Nevertheless, the association by type of skills shows a differentiate pattern. Prose skills are inversely related to responsibility positions. On the other hand, the higher quantitative skills the higher the probability to access to responsibility positions in job.

Table 4.7: Basic Skills and Job Hierarchy

People between 15 and 65 years old (non-students) who participate in labor market

(Marginal probabilities / robust test z are in brackets)

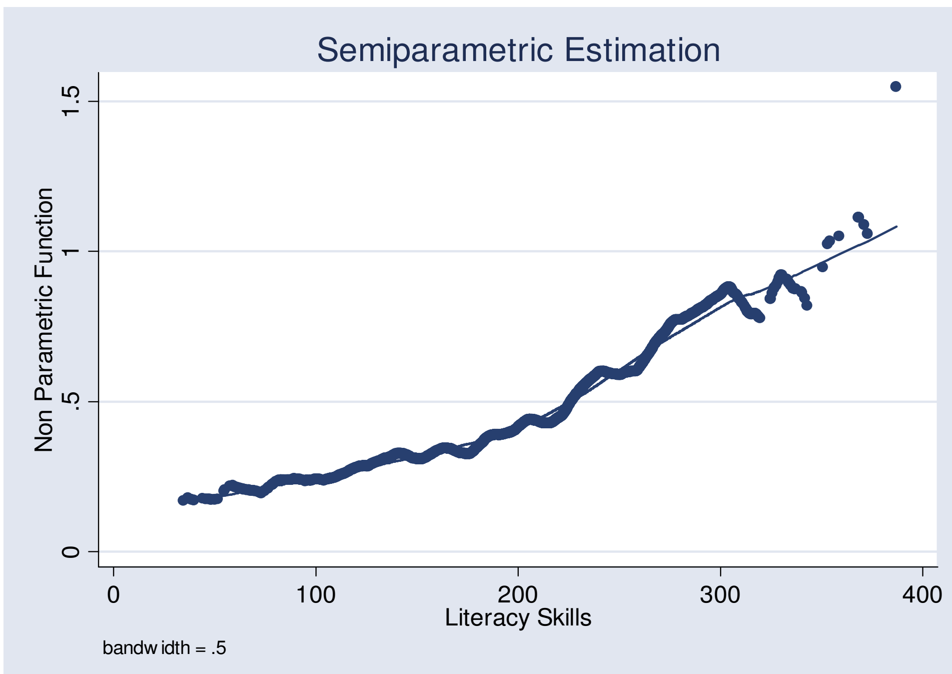
Variable	(1)	(2)	(3)	(4)	(5)
Average Literacy Skills:					0.0007
					[2.55]
Prose	-0.0022	-0.0021	-0.0020	-0.0029	
	[3.52]	[3.39]	[3.42]	[4.53]	
Document	-0.0002	-0.0001	-0.0002	-0.0001	
	[0.03]	[0.22]	[0.34]	[0.01]	
Quantitative	0.0026	0.0025	0.0024	0.0030	
	[4.79]	[4.44]	[4.53]	[5.21]	
Individual characteristics					
Years of Schooling	0.0280	0.0269	0.0242	0.0178	0.0194
	[7.36]	[7.12]	[6.22]	[3.84]	[4.14]
(Potential) Work Experience	0.0053	0.0017	0.0017	0.0032	0.0040
	[1.92]	[0.57]	[0.56]	[0.88]	[1.05]
Work Experience^2	-0.00004	0.0000	0.0000	-0.0001	-0.0001
	[0.65]	[0.20]	[0.26]	[0.77]	[0.82]
Hours of work	0.0020	0.0019	0.0012	0.0003	0.0004
	[3.05]	[2.87]	[1.61]	[0.33]	[0.45]
Male = 1		-0.0395	-0.0358	-0.0315	0.0009
		[1.58]	[1.46]	[1.08]	[0.03]
Head of household=1		0.0581	0.0490	0.0711	0.0811
		[2.09]	[1.78]	[2.34]	[2.58]
Single =1		-0.0314	-0.0344	-0.0161	-0.0334
		[1.22]	[1.35]	[5.50]	[1.12]
Some trainning=1			0.0679	0.0617	0.0685
			[2.52]	[2.00]	[2.17]
Upper quintile =1				0.0585	0.0633
				[2.13]	[2.26]
Job characteristics					
Full time work=1			0.0663	0.0772	0.0841
			[1.98]	[2.18]	[2.32]
Permantent work=1			0.0162	0.0154	0.0123
			[0.62]	[0.53]	[0.41]
Geographic characteristics					
Rural zone = 1				-0.0288	-0.0159
				[1.11]	[0.59]
Pseudo R2	0.15	0.16	0.17	0.17	0.14
Chi2 test	159.03	176.98	191.58	183.14	173.23
Observations	2124	2124	2124	1723	1723

Notes: Dependent variable is a dummy equal 1 if individual occupied a position of responsibility in his or her job.
Labor market participation includes those who have had some job in the last 12 months.
Upper quintile is a dummy variable equal 1 if individual belongs to top quintile of per capita income distribution.

Figure 4.6 shows the semi-parametric estimation of the relation between average skills and job hierarchy. Non linear relationship is not clear in this case, supporting the hypothesis of a positive linear relation between skills and the probability to access to responsibility positions.

Figure 4.6: Non-linear Relation between Job Hierarchy and Literacy Skills

People between 15 and 65 years old (non-students) who participate in labor market



4.4.2 Literacy Skills and Earnings.

This section seeks to quantify the relationship between literacy skills and earnings in the case of salaried workers. In this respect, it is natural to postulate that the capacity available for understanding and processing the content of documents, instructions, forms and other written material would naturally be linked to the labor productivity of the workers, as well as with the choice of best work alternatives, the adaptation to new work environments, mastering new technologies, etc.

An important problem in this matter is differentiating the effect of the skills with respect to the years of schooling. This is because we know that education increases human capital and, through this, labor productivity and the associated earnings. It is obvious that literacy skills are part of the human capital that education "produces". If there were a very close relation between both variables, then it would make no sense to study the impact of these skills on earnings, since the answer would already be given by the return on education.

Nevertheless, some factors exist that generate differences between both variables. Firstly, measuring education through years of schooling only partially captures the differences in the quality of the education, which can certainly be seen in educational outcome variables, such as what are the literacy skills at the moment of leaving school. Secondly, people can have abilities that are reflected in the literacy skills level, beyond the impact on years of schooling. Thus, within the cohort who enters the labor market after leaving secondary school, the differences in literacy skills would reflect to some extent differences in cognitive abilities. Thirdly, we have identified in the previous section that work practice also contributes to the formation of literacy skills, which introduces another gap between this variable and schooling.

Pryor and Schalaffer (1999) analyze the relation between functional literacy and earnings, even though the causal direction between both variables is not discussed in detail. It is shown that an increase in a standard deviation in the functional literacy level is associated with an increase of 3.5 to 7.2 per cent in the probability of being employed, as well as a 10 per cent increase in the salaries of the workers.

Two more specific studies are those of Rivera-Batiz (1994), who studies the impact of functional literacy (quantitative) on the probabilities of being unemployed taking the case of young adults in the United States, and Denny, Harmon and Redmond (2000), who analyze the effect of functional literacy on earnings in Great Britain, Northern Ireland and the Republic of Ireland. The results of these studies are in line with the other aforementioned studies. A higher skill level is associated with a lower probability of unemployment and with higher earnings levels, once the schooling effect is taken into account as well as the other variables related to labor market outcomes.

All previous studies are based on cross section information which makes treating the relation between labor market outcomes and functional literacy difficult. Other evidence available comes from data panel, which permit analyzing the relation between cognitive abilities, measured early on, and the subsequent work performance.

Along these lines, Murname, Willett and Levy (1995) studied the relation between basic cognitive abilities in the USA, measured through a basic math test at 18 years of age, and salaries achieved at 24 years of age. The authors concluded that there is evidence of increasing returns on ability in that country, after comparing measurements over different years. They also found that the results of the test are important predictors of subsequent educational achievement, measured as college graduations, and that they reduce the returns on education by between 40 and 50 per cent in a wage equation. This result is interpreted as arising from the inclusion of a previously omitted variable (ability).

Heckman and Vytlacil (2000) consider the difficulty in identifying the coefficients of education and abilities in a wage equation, given the strong correlation between both variables. This problem ("sorting bias") antecedes the traditional problem of omitted variables for abilities in wage equations.

Another example in this line of research is the work of Cawley et.al. (1996), who study the impact of ability on salaries using the National Longitudinal Young Survey. The authors consider the "g" factor or general intelligence as a measure of ability, defined as the first principal component of the ASVAB test results (Armed Services Vocational Aptitude Battery).14 The results show a "g" impact on salaries, controlling for years of schooling and other variables, even when the magnitude of the effect is lower. The coefficient or "return on ability" varies by gender-race categories, after controlling for occupational

14 It includes 10 subtests, including arithmetic reasoning, vocabulary knowledge, texts comprehension and mathematics knowledge.

choice, contrary to that postulated by the meritocratic hypothesis (salaries determined by ability and schooling, beyond race or gender).

In the Chilean case, information exists for only one point in time. As so defined, that makes difficult establishing a relationship between functional literacy and work performance. As such, for example, the data available does not allow a clear separation between the cohort effects and life-cycle effects; while identifying the effect of work experience on the development of literacy abilities requires assuming specific time patterns of the first variable.

Notwithstanding the aforementioned, it is possible to deduce important characteristics about the relation between functional literacy and job opportunities in the case of (non-student) workers between 15 and 65 years of age. The data points to a dynamic relationship between the development and the use of this type of basic skills, proving that schooling as well as work experience contributes to the development of this type of abilities. Meanwhile, higher literacy skills increase labor productivity and income in the case of low skilled workers. In the case of skilled workers, those skills have no effect on income levels beyond the already internalized component of years of schooling.

Our empirical approximation follows two complementary paths. First, we examine the impact that these skills have on earnings through a Mincer equation, controlling for years of schooling and potential experience. Secondly, we work with the residue of a regression between literacy skills and their observable determinants, in order to discover if some systematic relation exists between earnings and that part of the skills not captured by schooling, work experience and other variables.

We analyze the relation between skills and work performance for men and women between 15 and 65 years of age (non-students). We control for endogeneity in labor market participation decisions using similar specifications in Table 4.6.

4.4.2.1 Basic skills and earnings

The effect of basic skills on earnings is looked at through a Mincer equation. We use Heckman's approach to control for labor market participation decisions where selection equation is similar to presented in Table 4.6. Tables 4.8 and 4.9 present the results obtained, as much for the traditional specification as for that which permits estimating the return rates by level of schooling ("spline" regression type).

Table 4.8: Earnings Equations (Heckman's ML estimates)

Male salaried workers aged between 15 and 65 (non students)

(OLS, robust, test-t in parenthesis)

Dep. variable: Log wage	(1)	(2)	(3)	(4)
Years of schooling	0.1078	0.0783	0.0876	0.0542
	(13.82)	(8.02)	(4.28)	(2.53)
Secondary education (spline)			-0.0013	0.0012
			(0.05)	(0.04)
Higher education (spline)			0.0731	0.0764
			(2.68)	(2.84)
Literacy skills		0.0029		0.0030
		(4.91)		(5.07)
(Potential) work experience	-0.0008	0.0018	0.0019	0.0047
	(0.12)	(0.27)	(0.28)	(0.69)
Work experience^2	0.0003	0.0003	0.00026	0.0002
	(2.69)	(2.22)	(1.94)	(1.40)
Hours of work	0.0249	0.0252	0.0253	0.0256
	(12.53)	(12.73)	(12.71)	(12.96)
Constant	11.8573	11.4802	11.9933	11.6261
	(88.28)	(75.07)	(63.81)	(58.22)
Log likelihood	-1146	-1134	-1141	-1128
Censored observations	67	67	67	67
Uncensored observations	882	882	882	882

Table 4.9: Earnings Equations (Heckman's ML estimates)

Female salaried workers aged between 15 and 65 (non students)

(OLS, robust, test-t in parenthesis)

Dep. variable: Log wage	(1)	(2)	(3)	(4)
Years of schooling	0.1032	0.0840	0.0498	0.0124
	(8.73)	(5.93)	(1.55)	(0.33)
Secondary education (spline)			0.0292	0.0424
			(0.77)	(1.10)
Higher education (spline)			0.0846	0.0893
			(2.52)	(2.68)
Literacy skills		0.0019		0.0024
		(2.45)		(3.04)
(Potential) work experience	0.0181	0.0186	0.0147	0.0137
	(1.91)	(1.97)	(1.26)	(0.97)
Work experience^2	-0.0001	-0.0001	-0.00007	-0.0001
	(0.45)	(0.51)	(0.22)	(0.15)
Hours of work	0.0226	0.0226	0.0218	0.0214
	(10.83)	(10.85)	(9.34)	(7.97)
Constant	11.5062	11.2794	12.0250	11.8807
	(50.00)	(45.57)	(28.07)	(21.35)
Log likelihood	-1117	-1114	-1111	-1107
Censored observations	292	292	292	292
Uncensored observations	581	581	581	581

The results show a positive and significant effect of basic skills on earnings. Ten extra points in the IALS test are associated with a 3 percentage point increase in salaries for men, once one controls for schooling, potential experience and the other factors considered in the regressions. In the case of women the effect is lower, such that ten extra points in the IALS test are associated with a 2 percentage point increase in salaries.

The inclusion of the skills in the earnings equations makes the returns on education drop by three points. This can reflect an effect of omitted variable, given that the variable "literacy skills" is positively related to years of schooling. Therefore, the schooling coefficient would be overestimated when there is no control for the variable "literacy skills".

It is important to note that the premium for higher education *is not* affected by the incorporation of the literacy skills variable. In this manner, the factors that underlie the higher return rate associated with higher education would be different to those related to the literacy skills.

An underlying problem in the earnings equations is a certain degree of endogeneity in the variable "literacy skills". That is, there may be common non-observables in the determination of the literacy skills and earnings. However, this same problem characterizes traditional earnings equations, given that there are non-observables that affect schooling as well as earnings. We do not possess instruments in the database that allow us to correct for eventual bias, therefore the results obtained must be interpreted with caution.

Another problem is caused by the strong correlation between schooling and literacy skills, which makes it difficult to identify the net impact of the skills on earnings. An alternative way of exploring the relation between earnings and literacy skills is via earnings equations conditional on levels of schooling. Tables 4.10 and 4.11 present this variant for salaried men and women who have between 8 and 12 years of schooling, respectively. These represent thresholds of education for which there are an adequate quantity of observations in the sample.

The results for these regressions confirm the positive impact of literacy skills on earnings. Within an educational cohort, a higher level of literacy skills seems associated with higher earnings.

It is interesting to note that the impact of literacy skills is more important for people with 8 years of schooling. The variable coefficient is more than three times higher than that showed by salaried men workers with 12 years of schooling. For women, the coefficient for salaried workers with 8 years of schooling is only two times higher than that showed by women with 12 years of schooling. This evidence points in the same direction as that indicated by the effect of the skills on the returns to education: that the effect of the skills on earnings would be particularly relevant for workers with lower educational qualifications.

Table 4.10: Earnings Equations conditional on schooling (Heckman's ML estimates)

Male salaried workers aged between 15 and 65 (non students)

(OLS, robust, test-t in parenthesis)

Dep. variable: Log wage	8 years of schooling		12 years of schooling	
Literacy skills		0.0071		0.0022
		(5.70)		(1.59)
(Potential) work experience	-0.0044	-0.0004	0.0509	0.0490
	(0.22)	(0.02)	(2.97)	(2.87)
Work experience^2	0.0002	0.0001	-0.0008	-0.0008
	(0.54)	(0.18)	(1.96)	(1.85)
Hours of work	0.0340	0.0312	0.0226	0.0233
	(6.55)	(6.64)	(5.03)	(5.21)
Constant	12.2140	10.9563	12.7919	12.2526
	(42.66)	(32.13)	(59.12)	(30.47)
Log likelihood	-162	-148	-169	-168
Censored observations	4	4	3	3
Uncensored observations	142	142	168	168

Table 4.11: Earnings Equations conditional on schooling (Heckman's ML estimates) Female salaried workers aged between 15 and 65 (non students) (OLS, robust, test-t in parenthesis)

Dep. variable: Log wage	8 years of schooling		12 years of schooling	
Literacy skills		0.0034		0.0017
		(1.67)		(0.87)
(Potential) work experience	0.0925	0.0961	0.0274	0.0281
	(1.70)	(1.55)	(1.33)	(1.35)
Work experience^2	-0.0016	-0.0017	-0.0003	-0.0003
	(1.50)	(1.38)	(0.50)	(0.50)
Hours of work	0.0338	0.0319	0.0248	0.0246
	(6.18)	(5.98)	(5.21)	(5.16)
Constant	10.5256	9.9024	12.5201	12.1219
	(15.00)	(11.34)	(44.59)	(22.56)
Log likelihood	-96	-94	-228	-228
Censored observations	41	41	24	41
Uncensored observations	56	56	144	56

4.4.2.2 "Residual Skills"

The impact of the skills on earnings gets confused the effect of schooling, work experience and other variables related to literacy skills. This section analyzes the residuals of a regression between skills and its determinants, for which we consider the specification (4) of the regression presented in Table 4.5. The procedure is the same as supposing that the correlation between schooling and skills is totally attributed to the first variable, as would also be the case for the other variables included in the regression. Thus, the residuals correspond to that part of the skills no related to those. The relation of the new variable with earnings represents a "floor" of the work impact of the skills.

To examine the relationship of interest, quartiles of the distribution of the residuals are computed. In Table 4.12, the relation between earnings, periods of schooling and the aforementioned quartiles of the residual skills is presented. The data presents a relatively clear pattern, delineating a positive relation between earnings and “residual” skills for workers with less than twelve years of schooling. On the other hand, the relation between earnings and residual skills dissipates for people with twelve years of education and over.

These results are consistent with the evidence from the earnings equations above. Moreover, they give robustness to those results, since in this occasion parameters that could have estimate biases are not used.

Table 4.12: Median salary, by schooling and residuals

Residual quartiles	Years of schooling				
	0-4	5-8	9-11	12	13 and over
1	720.0	840.0	1200.0	2400.0	2400.0
2	864.0	1000.0	1500.0	1680.0	3000.0
3	1020.0	1200.0	1440.0	1700.0	2400.0
4	1200.0	1200.0	1800.0	2160.0	2400.0
Total	880.0	1080.0	1500.0	1920.0	2400.0

It follows that the type of abilities related to literacy skills would be more important for explaining different productivity levels in lower skilled jobs. On the other hand, they would be less significant for jobs taken by people with higher education, since another type of ability (professional) seems to dominate.

Table 4.13 relates schooling and the residual skill quartiles with the skill levels. Each cell contains the same people as the previous table (earnings). In this case, we can see substantial variance in the literacy skills of the different schooling categories. Nevertheless, this only translates into earnings variations in the lower education levels. In the case of people with higher education, sharp literacy skill differences can be seen that do not relate to differences in earnings.

Table 4.13: Average skills, by schooling and residuals

Residual quartiles	Years of schooling				
	0-4	5-8	9-11	12	13 and over
1	96.2	126.3	167.7	188.3	217.3
2	123.0	171.8	208.6	223.9	257.6
3	157.8	206.6	231.6	250.7	285.9
4	203.8	240.4	272.4	286.0	313.8
Total	147.7	185.0	220.6	236.3	271.3

The aforementioned conclusion continues to be valid after controlling for the other determinants of earnings (Tables 4.14 and 4.15). Thus, the positive effect of "residual" skills on the earnings of low skilled workers is verified, and to a lesser extent for intermediate skilled workers. There are no effects for workers with higher education. When the sum of workers is considered the differential effects by level of education are not significant.

Table 4.14: Earnings Equations (Heckman's ML estimates)

Salaried male workers aged between 15 and 65 (non students)

(OLS, robust, test-t in parenthesis)

Dep. variable: Log wage	(1)	(2)	(3)
Years of schooling	0.1079	0.1061	0.1066
	(14.39)	(14.21)	(14.30)
(Potential) work experience	0.0163	0.0154	0.0153
	(6.73)	(6.39)	(6.36)
Hours of work	0.0245	0.0249	0.0247
	(12.32)	(12.55)	(12.49)
Residual skills		0.0024	0.004
		(3.92)	(4.24)
Skills*D1			-0.0022
			(1.66)
Skills*D2			-0.0012
			(0.67)
Constant	11.7345	11.7479	11.7546
	(93.06)	(93.65)	(93.95)
Log likelihood	-1150	-1142	-1140
Censored observations	67	67	67
Uncensored observations	882	882	882

Note: D1: dummy equals 1 if individual has secondary education
D2: dummy equals 1 if individual has higher education

Table 4.15: Earnings Equations (Heckman's ML estimates)

Salaried female workers aged between 15 and 65 (non students)

(OLS, robust, test-t in parenthesis)

Dep. variable: Log wage	(1)	(2)	(3)
Years of schooling	0.1055	0.1010	0.0998
	(10.82)	(10.38)	(10.22)
(Potential) work experience	0.0182	0.0168	0.0164
	(4.88)	(4.63)	(4.50)
Hours of work	0.0210	0.0202	0.0206
	(9.40)	(9.18)	(9.36)
Residual skills		0.0012	0.003
		(1.56)	(2.24)
Skills*D1			-0.0031
			(1.76)
Skills*D2			0.0014
			(0.67)
Constant	11.6281	11.7600	11.7600
	(70.95)	(72.14)	(72.41)
Log likelihood	-1133	-1113	-1111
Censored observations	292	292	292
Uncensored observations	581	581	581

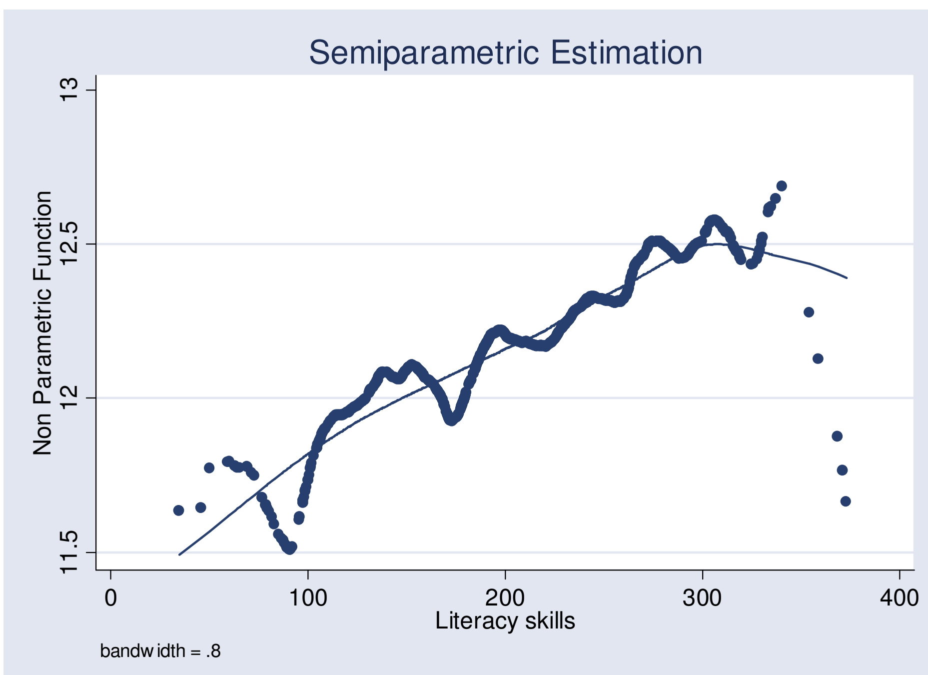
Note: D1: dummy equals 1 if individual has secondary education

D2: dummy equals 1 if individual has higher education

Finally, Figure 4.7 shows the results of semiparametric estimations of the relationship between earnings and basic skills based on specification 4 in Table 4.8. We can observe that, in general, the relation is non linear and, particularly, concave. That is, there is a premium to basic skills until certain level, beyond which probably more qualified skills are rewarded.

Figure 4.7: Non-linear Relation between Earnings and Literacy Skills

Salaried workers aged between 15 and 65 (non students)



4.4.3 Literacy Skills and Poverty

This section seeks to econometrically evaluate the hypothesis that basic skills produce a separation between people who live under the poverty line and those over the poverty line. For this, we define the dichotomous variable poverty equals to 1 if the person lived in a household that live under the poverty line. The latter is defined as the cutoff of the per capita income cumulative distribution for households at the 30th percentile

Table 4.16 presents results of probit model estimations. We include additional controls such as age, gender, marital status, schooling, parental education, training and geographic zone.

The evidence shows that schooling and training significantly reduces the probability of fall in poverty. Mother's education seems not affect poverty condition, whereas higher father's schooling is associated to a lower probability of fall in poverty. With respect to gender, men are less vulnerable to poverty than women.

Finally, controlling by human capital and many other characteristics, we find that better average basic skills reduce the probability of being classified as poor (specification 5). In particular, ten additional points in average IALS score is associated with a 0.6 percentage points decrease in this probability. We do not observe significant individual effects of the different types of skills on the probability of fall in poverty.

Table 4.16: Basic Skills and Poverty

People between 15 and 65 years old (non-students)

(Marginal probabilities / robust test z are in brackets)

Variable	(1)	(2)	(3)	(4)	(5)
Average Literacy Skills:					-0.0006
					[1.97]
Prose	-0.0006	-0.0005	-0.0004	-0.0003	
	[0.99]	[0.80]	[0.64]	[0.53]	
Document	0.0011	0.0009	0.0007	0.0006	
	[1.54]	[1.19]	[0.89]	[0.74]	
Quantitative	-0.0013	-0.0010	-0.0007	-0.0007	
	[2.42]	[1.72]	[1.11]	[1.07]	
Individual characteristics					
Years of Schooling	-0.0293	-0.0230	-0.0230	-0.0228	-0.0232
	[7.80]	[5.81]	[5.09]	[5.01]	[5.15]
Age	-0.0018	-0.0014	0.0004	-0.0001	-0.00003
	[0.31]	[0.22]	[0.06]	[0.01]	[0.00]
Age^2	-0.00002	-0.00001	-0.00004	-0.00004	-0.00004
	[0.23]	[0.20]	[0.56]	[0.51]	[0.55]
Male = 1		-0.0816	-0.0961	-0.0937	-0.0966
		[2.82]	[3.21]	[3.12]	[3.32]
Head of household=1		0.0129	0.0202	0.0220	0.0228
		[0.44]	[0.65]	[0.70]	[0.73]
Single =1		-0.0097	0.0112	0.0100	0.0136
		[0.33]	[0.36]	[0.32]	[0.45]
Some trainning=1		-0.0753	-0.0620	-0.0629	-0.0621
		[2.68]	[2.08]	[2.11]	[2.05]
Parental education					
Mother's educational level			0.0016		
			[0.34]		
Father's educational level			-0.0087		
			[2.13]		
Average parental educational level				-0.0080	-0.0086
				[1.90]	[2.06]
Geographic characteristics					
Rural zone = 1		0.2080	0.1690	0.1687	0.1697
		[8.13]	[5.91]	[5.89]	[5.93]
Pseudo R2	0.14	0.18	0.20	0.20	0.20
Chi2 test	222.25	347.37	273.65	267.52	259.95
Observations	2554	2554	1985	1985	1985

Notes: Dependent variable is a dummy equal 1 if household per capita income is below the poverty line and 0 if not.

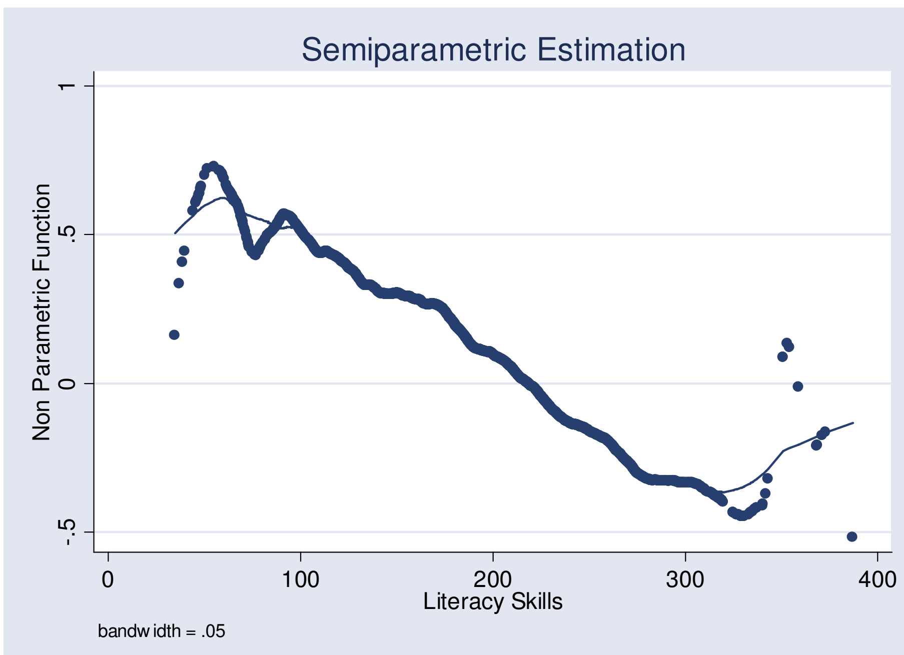
Poverty line is defined as the cutoff of the cumulative distribution of households at the 30th percentile.

Some trainnig is a dummy variable equal 1 if individual has receive some educational or training course in the last 12 months.

Figure 4.8 shows the semiparametric estimation result for relation between basic skills and poverty, using specification 5 in Table 4.16. We can observe a cubic pattern with stronger negative relation in the intermediate segments of literacy skills distribution than in the tails.

Figure 4.8: Non-linear Relation between Poverty and Literacy Skills

People between 15 and 65 years old (non-students)



4.5. Quality of Education and Quality of Life: Conclusions

Chile was the first developing country in which the international adult literacy skills survey (IALS) was carried out back in 1998. This article explores the relationship between literacy skills, defined as the capacity to understand and process information from written texts, and diverse indicators of quality of life for people between 15 and 65 years of age.

The chapter has shown the importance of basic skills, measured by the individuals' performance in the IALS test score, to predict occupational position in work, earnings and poverty. In particular, we find significant positive effects of average literacy skills on labor participation and the access to responsibility positions in job. Quantitative skills are found more important than prose and document skills for this probability. We also find significant negative effects of average literacy skills on poverty condition.

Additionally, a greater literacy skill level is associated with higher earnings, once schooling and other earnings related variables are taken into account. The type of abilities related to the literacy skills would be more important for explaining the different productivity levels of people with primary and secondary education. However, it would be less significant in jobs taken by people with higher education, where other types of abilities seem to explain the salary differences within this group.

The chapter has also shown that a two-way relation exists between the literacy skills and the work performance, indicating the existence of a dynamic relationship between the formation of skills and their use at work.

Consistent with previous studies, we find that principal determinant of the level of literacy skills is the years of schooling. The results indicate that each additional year of schooling increases the basic skill level. The linear relation between schooling and literacy skills contrasts with the relation between schooling and earnings which is heavily convex given the greater rates of return of higher education.

Schooling determines the initial skills level of people. This variable evolves over time depending on the work use of those skills. The resulting skill level reflects the interaction of schooling with the practice of those skills in the work context.

Thus, workers with low education enter jobs that do not require the use of literacy skills; this in turn helps explain the decline in those skills of that group over time. As schooling increases, the initial skill level also grows and its use in work also increases throughout the work cycle, suggesting the existence of a dynamic relationship between skill level and its use in work.

5. International Benchmarking

5.1 The PISA assessments in Chile

PISA is an international assessment program that evaluates the reading, mathematics and science literacy of 15 year olds in grades 7th to 12th. Chile has participated in two rounds of PISA evaluations: 2000 and 2006. In the year 2000, when the PISA test had its focus on reading, results showed that Chilean students had reading, math and science skills far below the OECD average, but similar to those of other Latin American countries that took the test that year, such as Argentina and México. Of the five performance levels specified by PISA, thirty percent of Chilean students reached level 2 in 2000, meaning that they can identify the main idea in a text and extract fragments of information, and only five percent reached level 4, which means they can make inferences and critically evaluate what they read. Although Chilean results in PISA 2000 showed a strong effect of socioeconomic status, Chilean students from the socioeconomic elites still did not reach the performance levels of similar students in developed countries such as USA, Finland and Portugal (Mineduc, 2004).

Very recently, data from the 2006 PISA assessment has been released, allowing us to add to the existing analyses on PISA 2000 with this new data. Therefore, for the international benchmarking chapter we will use the recently released data from PISA 2006. Five other Latin American countries took this assessment in 2006 (Mexico, Argentina, Colombia, Uruguay and Brazil), and Chile's performance will be compared mostly to that of these countries.

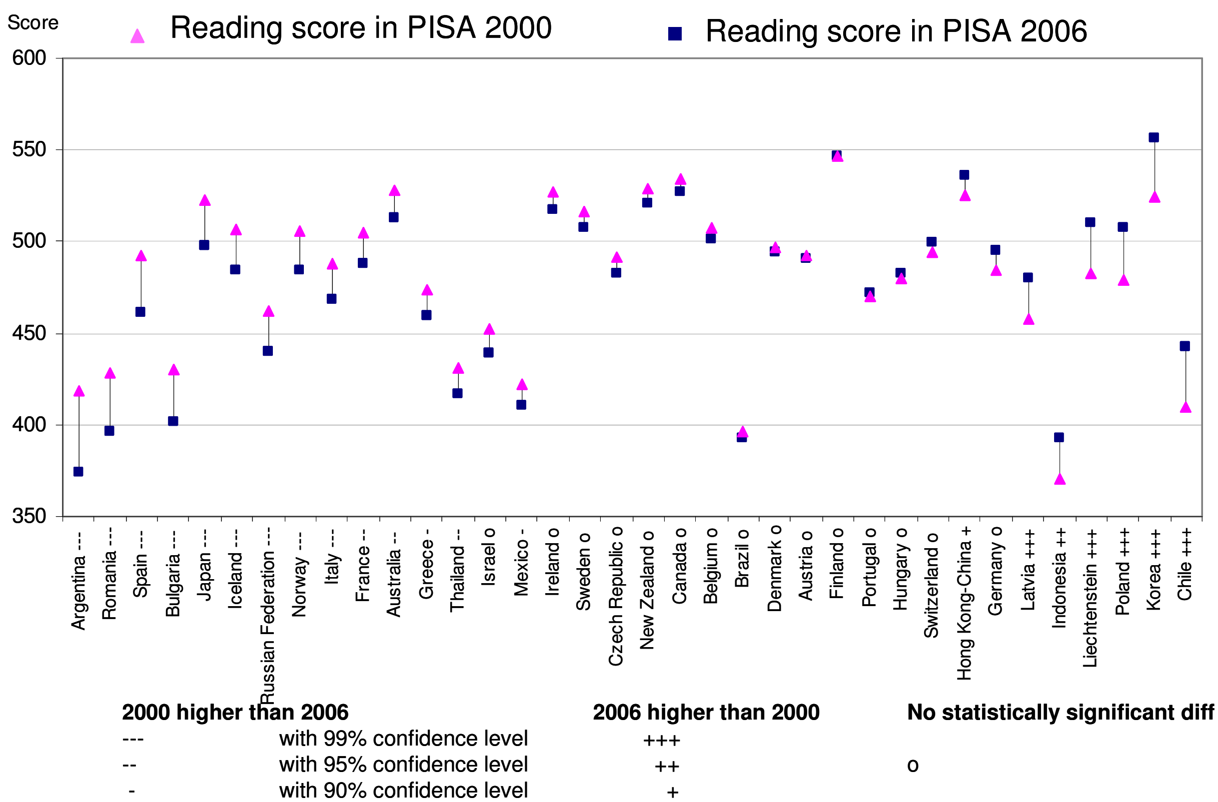
5.2 Reading

Although PISA 2006 had a focus on science, it also included reading and math evaluations that are comparable with the reading assessment of 2000 and with the math assessment of 2003 (OECD, 2007). This allows us to examine possible variations in the Chilean reading score and in Chile's relative position with respect to other countries taking the test in these two dates. Figure 5.1 shows the performance of countries in reading in the two PISA assessments of interest (when available).

As the figure shows, Chile registered the largest increase in reading scores of all participating countries, and it was the only Latin American country, of those that participated in both years, that increased its score (Colombia only participated in 2006, and Uruguay, which participated in both PISA 2003 and 2006, registered a decrease in their scores between the two dates).

Figure 5.1

Differences in Reading score of countries participating in PISA 2000 and 20006



Countries are ranked in ascending order of score difference between PISA 2006 and PISA 2000.
Source: OECD PISA database 2006, Table 6.3a.

In spite of its increase, Chile continues to rank very low with respect to all participating countries, and it still shows very low percentages of students at the top proficiency levels. Nevertheless, its reading performance is now the highest of the participating Latin American countries. Table 5.1 shows the distribution of students in the five PISA proficiency levels across Latin American countries in 2000 and 2006, when available (Uruguay's 2003 reading score is used instead of 2000).

Table 5.1

Percentage of students at each proficiency level on the reading scale in 2000 and 20006, Latin American countries

	Proficiency levels											
	Below Level 1 (below 334.75 score points)		Level 1 (from 334.75 to 407.47 score points)		Level 2 (from 407.47 to 480.18 score points)		Level 3 (from 480.18 to 552.89 score points)		Level 4 (from 552.89 to 625.61 score points)		Level 5 (above 625.61 score points)	
	2000	2006	2000	2006	2000	2006	2000	2006	2000	2006	2000	2006
Mexico	16	21,0	28	26,0	30	28,9	19	18,2	6	5,3	1	0,6
Argentina	23	35,8	21	22,1	25,5	21,8	20,3	14,3	8,6	5,1	1,7	0,9
Brazil	23,00	27,8	33,00	27,7	28,00	25,3	13,00	13,4	3,00	4,7	0,5	1,1
Chile	20,00	14,8	28,00	21,5	30,00	28,0	16,60	21,1	4,80	11,0	0,5	3,5
Uruguay (2003)	21,00	25,3	19,00	21,3	23,90	23,4	19,80	18,0	11,20	8,9	5,3	3,1

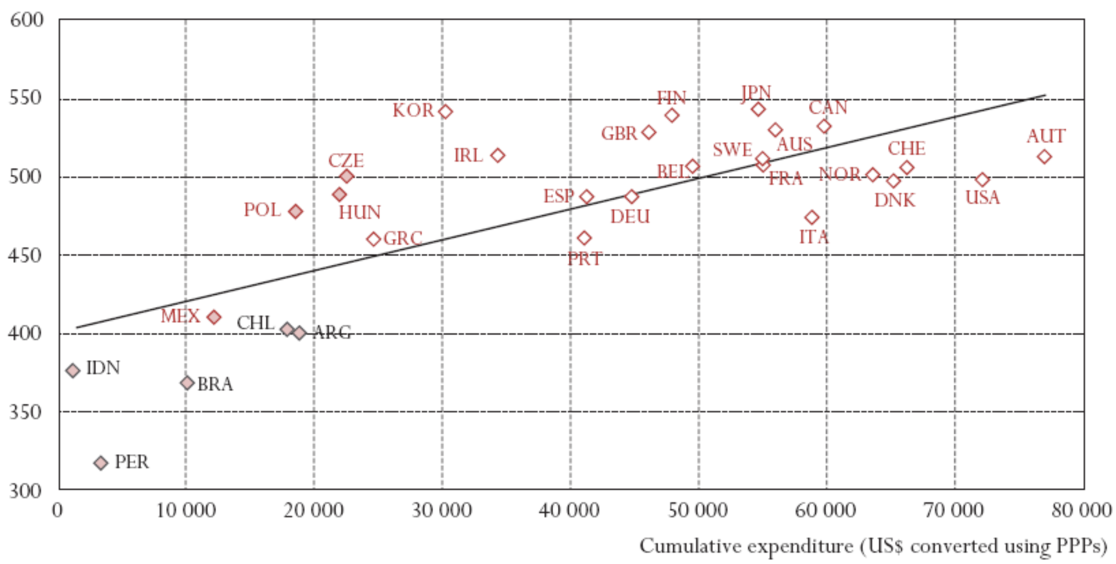
Source: OECD PISA database 2006, Table 6.1a., OECD (2002).

Does Chile's increase in reading scores represent an improvement in efficiency? Using decomposition techniques with PISA 2000 data, Paredes & Ruiz (2007) found that Chile performed inefficiently in comparison to other Latin American countries, that is, that given Chilean students' characteristics and school inputs, our students obtained lower results in PISA than similar students would have obtained in similar schools in Brazil, Argentina and Mexico. This inefficiency is also portrayed in Figure 5.2, which shows the relation between the PISA 2000 combined reading, science and math scores, and educational expenditure per student up to 15 years of age. As shown in the figure, in 2000 all Latin American countries had lower scores than expected given their expenditure per student, including Chile. However, the situation in 2006 seems to have changed. Figure 5.3 shows the relation between per-student spending in 2004 (primary plus secondary levels), and PISA 2006 reading scores. We can observe that here Chile is right on the tendency line, while all other

Latin American countries remain below it, showing lower scores than expected. This may support the hypothesis that Chile's increased reading scores represent higher efficiency.

Figure 5.2

Average performance in 2000 PISA (combined reading, mathematics and science scales) and cumulative expenditure on educational institutions up to age 15 in US$, converted using purchasing power parities

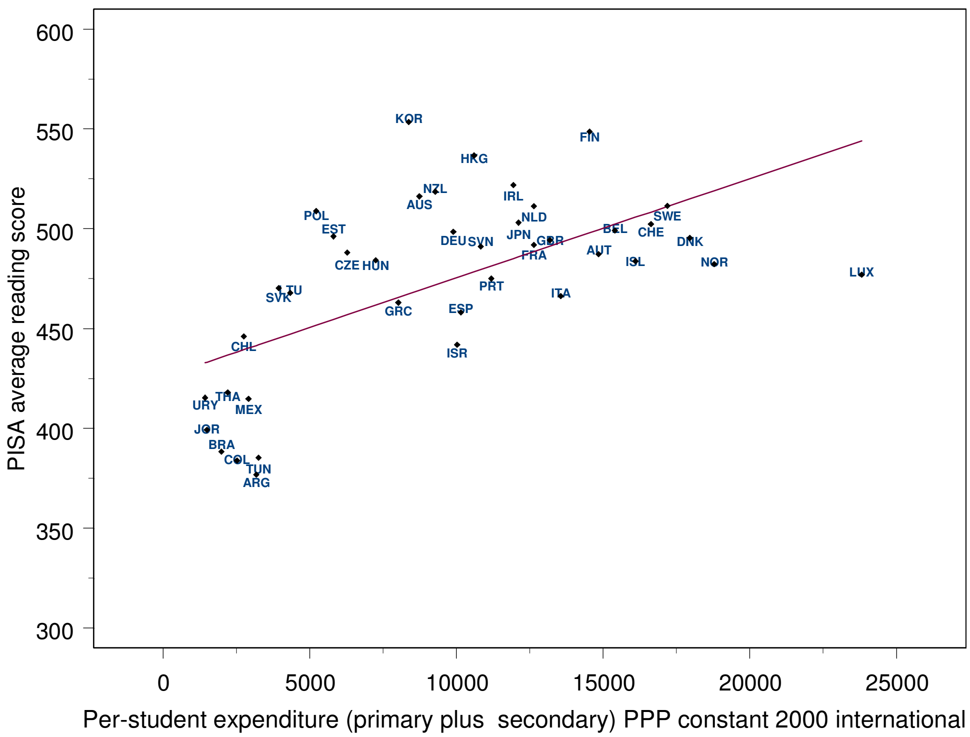


Source: OECD PISA database, 2003. Table 3.3.

Figure 5.3

2004 per-student spending (primary plus secondary)

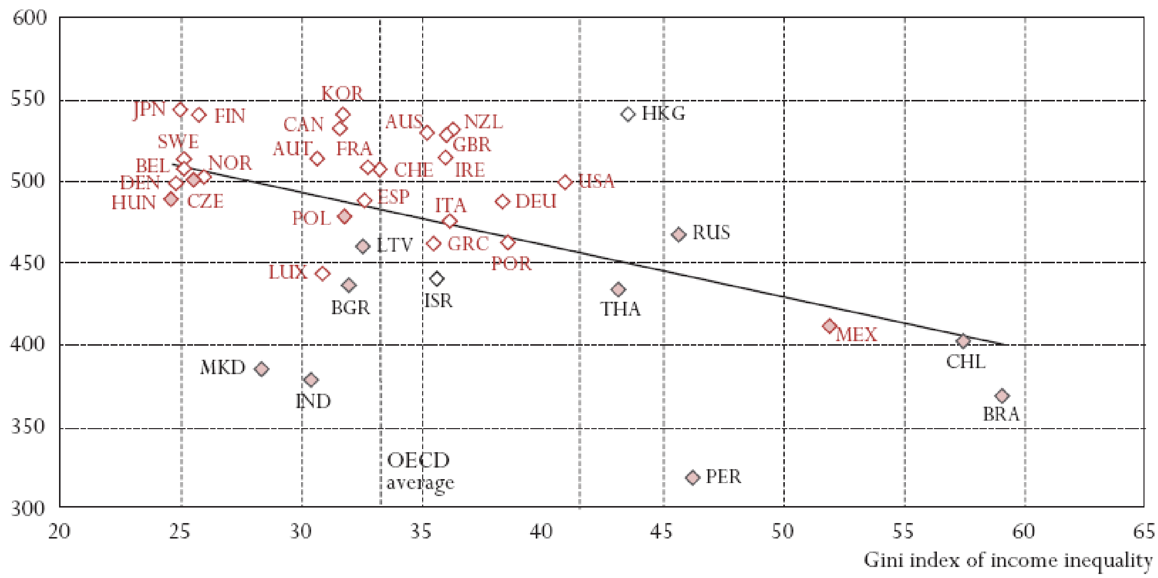
and PISA 2006 scores



A similar situation occurs when one examines the relationship between income inequality and PISA 2000 and 2006 scores. Figures 5.4 and 5.5 show the relationship between PISA 2000 and 2006 scores and the corresponding Gini index. Here Chile performs better than expected in reading in 2006, while in 2000 it obtained lower scores than it should have given its level of income inequality.

Figure 5.4

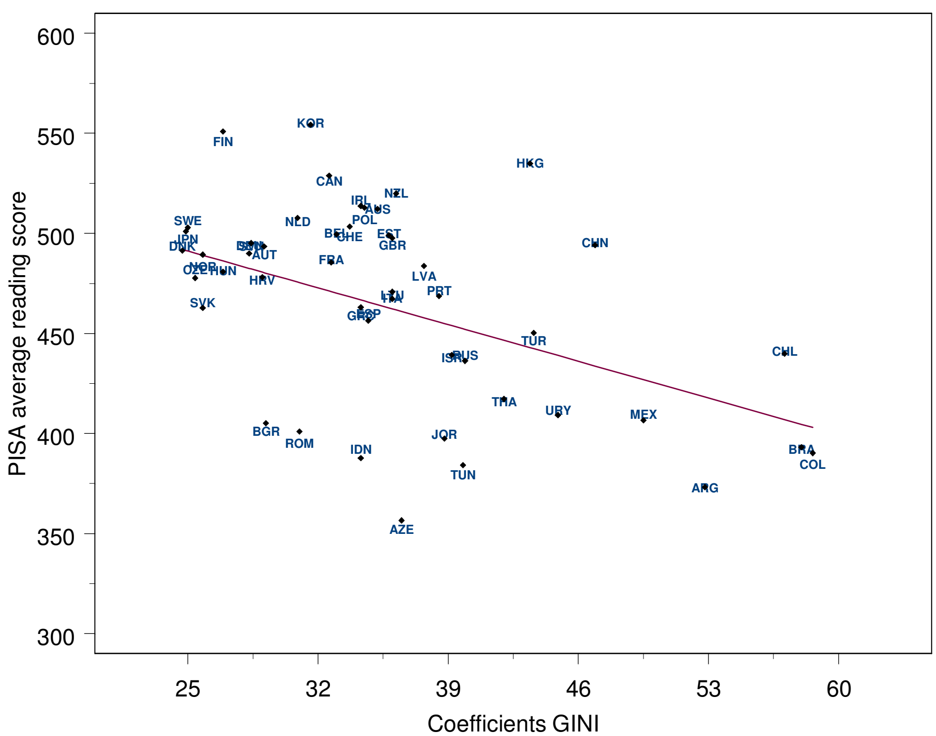
Gini index and PISA 2000 combined math, science and reading scores



Source: OECD PISA database, 2003. Tables 1.4 and 3.3.

Figure 5.5

Gini index and PISA 2006 reading scores



5.3 Mathematics

In Mathematics, Chile performed second among the six participating Latin American countries, as shown in table 5.2. Within this group, Chile was outperformed only by Uruguay, although when compared with the complete group of countries that took the assessment, it ranked number 37.

Table 5.2

Mean mathematics score of the six Latin American countries participating in PISA 2006.

	Mean	S.E.
Argentina	381	(6,2)
Brazil	370	(2,9)
Chile	**411**	**(4,6)**
Colombia	370	(3,8)
Mexico	406	(2,9)
Uruguay	427	(2,6)

When examining the relationship between spending and scores, again Chile is located on the tendency line (Figure 5.6), and the same happens for the relationship between inequality and the scores (Figure 5.7), contrary to what occurred with the 2000 results (figures 5.2 and 5.4).

Figure 5.6

Per-student spending, primary plus secondary, and PISA 2006 Mathematics score

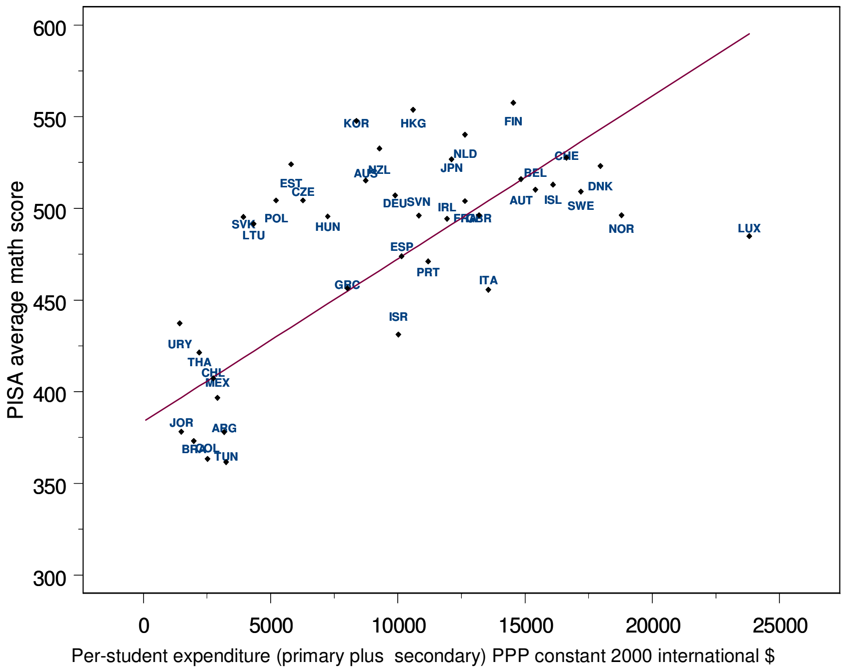
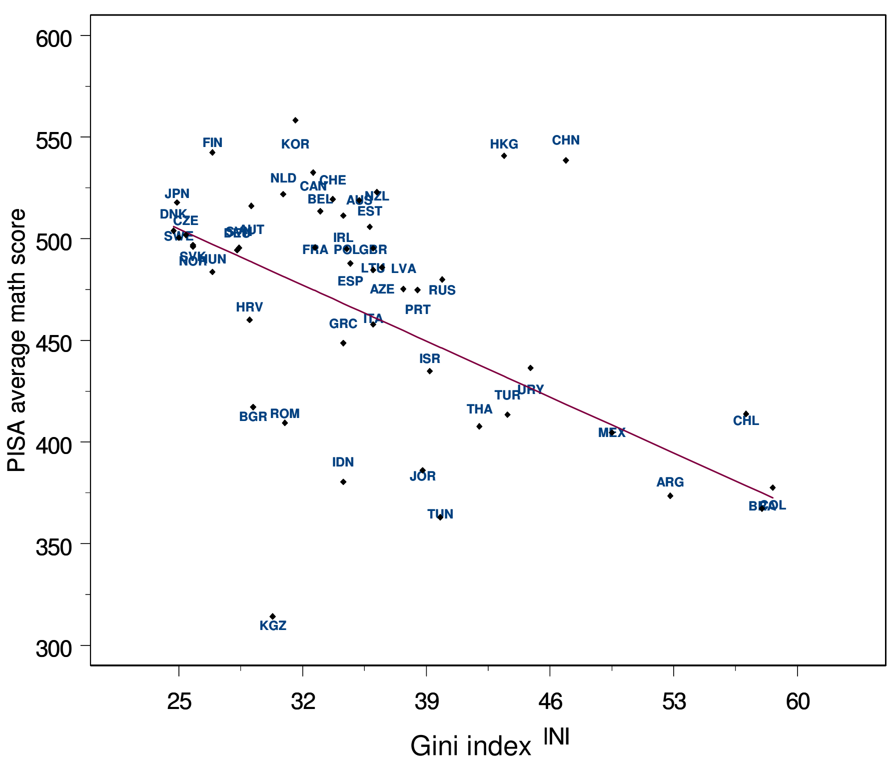


Figure 5.7

Gini Index and PISA 2006 Mathematics score



5.4 Science

The major focus of the PISA 2006 assessment was on science, meaning not only that the test evaluated science skills thoroughly, but also that the analysis of results is more extensive. This allows us to look not only at average scores, but also at the role that the socioeconomic status of individuals and schools plays in each of the six Latin American countries. Unfortunately, although Chile does have one previous assessment in science (2000), this is not comparable with the 2006 assessment (OECD, 2007).

Table 5.3 shows mean scores in science for the six participating Latin American countries. As in reading, Chile's science performance is the highest of the six countries, even though among the complete group it ranks only at 42. As it happened with reading and mathematics, Chile's scores in science are as expected or above expected, given its per-student spending and income inequality, as shown in figures 5.8 and 5.9, and contrary to what is shown in figures 4.2 and 4.4 for 2000 scores.

Table 5.3

Mean average scores in science for the six Latin American countries

	Mean	S.E.
Argentina	391	(6,1)
Brazil	390	(2,8)
Chile	**438**	**(4,3)**
Colombia	388	(3,4)
Mexico	410	(2,7)
Uruguay	428	(2,7)

Figure 5.8

Per-student spending, primary plus secondary,

and PISA 2006 Science score

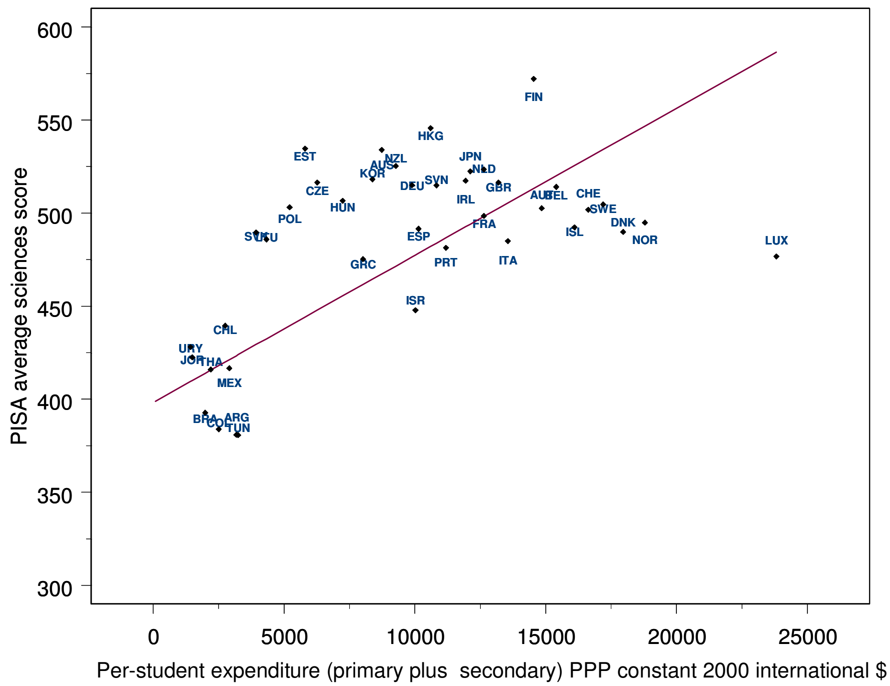
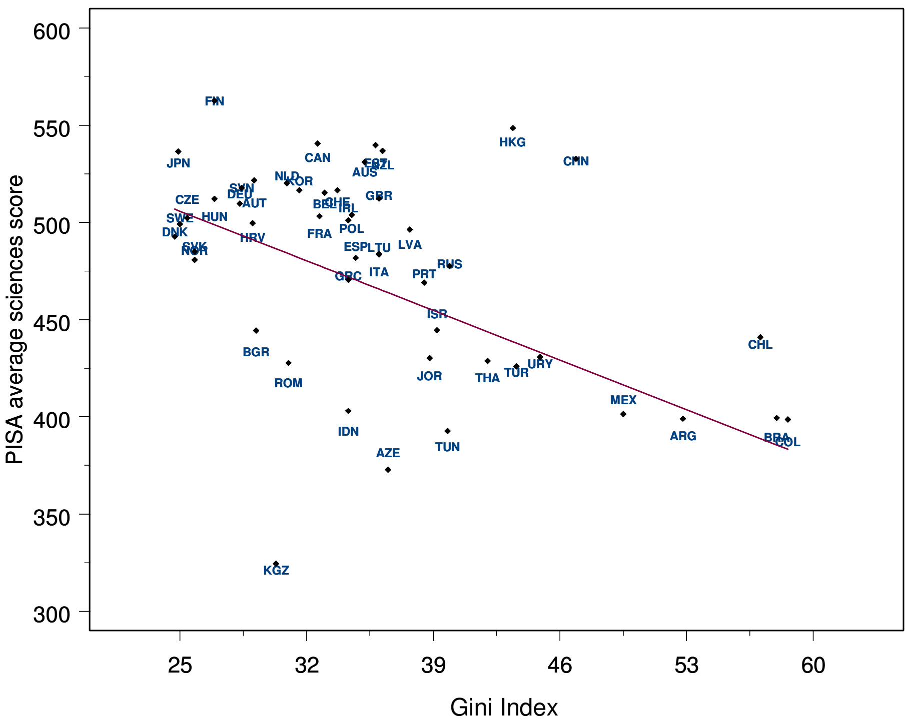


Figure 5.9

Gini Index and PISA 2006 science scores

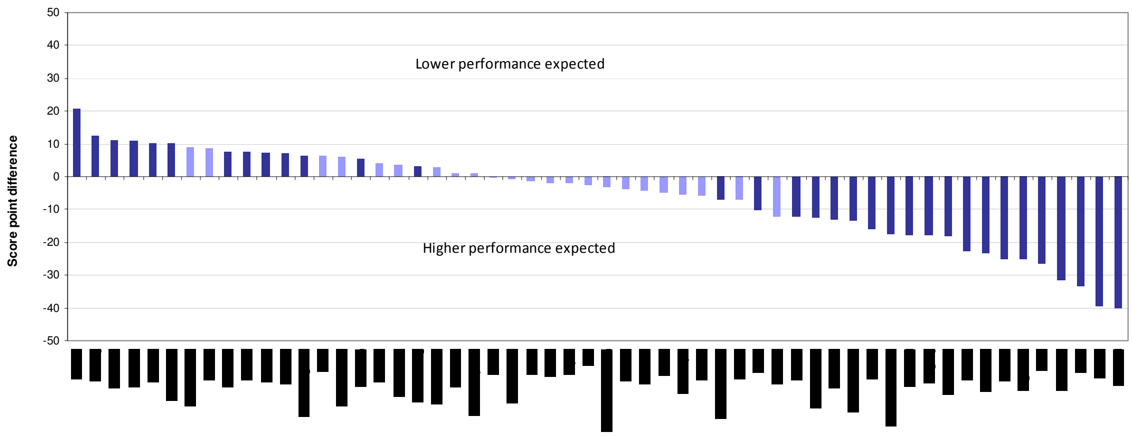


Although this may be an indicator that Chile is performing efficiently according to its general economic conditions, when taking into account the characteristics of students taking the test, Chilean scores look much lower than they should be. For example, when computing the difference between the observed country means and the mean that each country would have obtained if all countries had the same students with regards to their SES, Chile is one of the countries where the difference between observed and expected is the largest. That is, the average score of Chilean students who have a score in the socioeconomic index equal to the average socioeconomic index of OECD countries, perform much worse than similar students in other countries. This is portrayed in figure

5.10, where there are only four countries that have larger differences between observed and expected means than the one observed in Chile (Indonesia, Brazil, Turkey and Thailand).

Figure 5.10

Difference between the unadjusted mean score and the mean score on the science scale if the PISA mean index of economic, social and cultural status



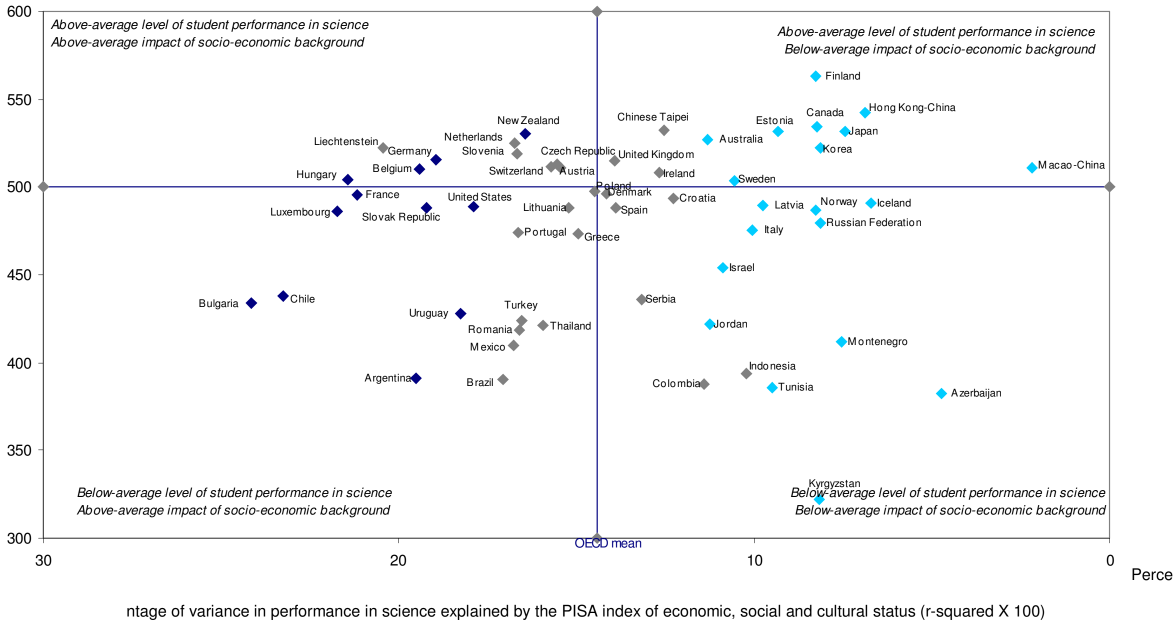
Countries are ranked in descending order of the difference between the unadjusted mean score and the mean score if the mean PISA index of economic, social and cultural status would be equal in all OECD countries. Statistically significant differences are marked in a darker tone.

Source: OECD PISA 2006 database, Table 4.4a.

The impact of socioeconomic status is also higher in Latin American countries than in the rest of the countries, and this is also valid for Chile. Figure 5.11 shows variation in the SES slopes (gradients) on science scores in all the countries, showing that all Latin American countries except Colombia have larger than average effects of SES in science scores.

Figure 5.11

Performance in science and the impact of socio-economic background

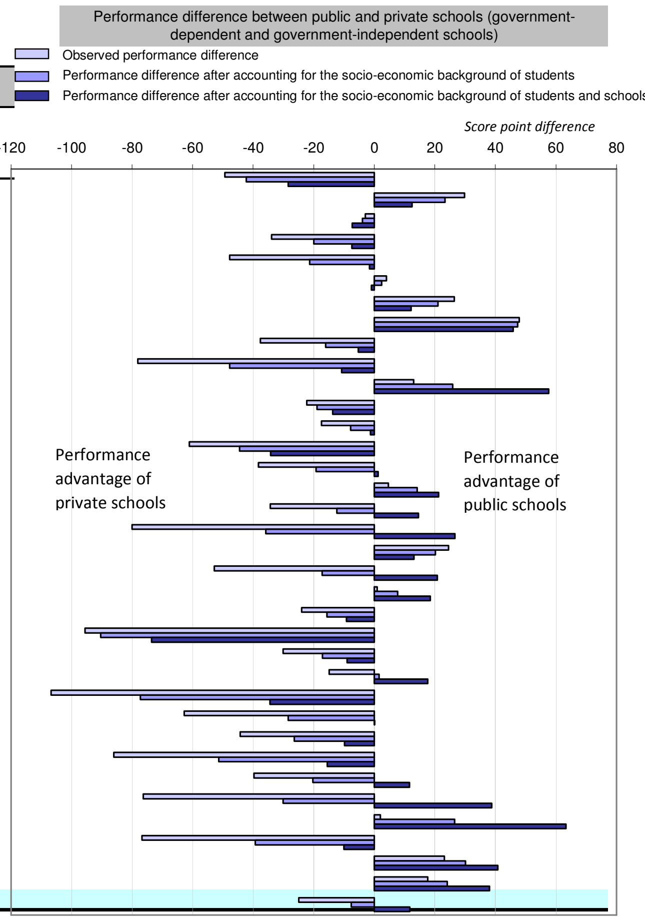


Note: OECD mean used in this figure is the arithmetic average of all OECD countries.
Source: OECD PISA 2006 database, Table 4.4a

This may be worsened in Chile by the strong school segregation by SES which, as we found in chapter 3 of this report, may be creating compositional effects that actually enlarge the gaps between the rich and the poor. The high segregation of the Chilean school system is partially shown in figure 5.12, which portrays the unadjusted differences between public and private schools, and the differences after adjusting by individual SES and school SES. As shown in this 5.12, introducing the individual SES index reduces differences between public and private schools in Chile in about one half, while introducing school SES practically makes them disappears.

Figure 5.12

Observed and adjusted differences between public and private schools, after accounting for individual and school SES



	Percentage of students enrolled in public schools	Percentage of students enrolled in private schools	
		Government-dependent	Government-independent
Macao-China	4	69	28
Hong Kong-China	7	91	2
Netherlands	33	67	0
Ireland	42	55	3
Chile	47	45	8
Korea	54	32	15
Indonesia	61	13	26
Chinese Taipei	65	0	35
Spain	65	25	10
Argentina	67	25	8
Japan	70	1	29
Israel	73	20	6
Denmark	76	23	1
Jordan	81	1	18
Colombia	83	5	12
Thailand	83	6	10
Hungary	84	13	3
Uruguay	85	0	15
Luxembourg	86	14	0
Mexico	90	0	10
Austria	91	8	1
Portugal	91	7	2
Qatar	91	0	9
Sweden	92	8	0
Slovak Republic	92	7	0
Brazil	92	0	8
United States	93	1	7
Canada	93	4	3
United Kingdom	94	0	6
Germany	94	6	0
Greece	95	0	5
Switzerland	95	1	4
New Zealand	96	0	4
Czech Republic	96	4	0
Italy	96	1	2
OECD average	86	10	4

Source: OECE PISA 2006 database, Table 5.4

5.5. Gender differences in reading, science and math

In spite of Chile's advantage in PISA 2006 scores in comparison with its Latin American neighbors, there is one indicator where performance is lagging behind the other five countries, which is gender equity. Together with having high average scores (relative to Latin American countries), Chile also shows the largest differences in favor of males in math and science, and the smallest differences in favor of women in reading, in a very atypical pattern that is clearly disadvantageous to female students (Tables 5.4, 5.5 and 5.6).

Table 5.4

Mean score, variation and gender differences in student performance on the science scale

	All students				**Gender differences**					
	Mean score		**Standard deviation**		**Males**		**Females**		**Difference (M - F)**	
	Mean	S.E.	S.D.	S.E.	Mean score	S.E.	Mean score	S.E.	Score dif.	S.E.
Argentina	391	(6,1)	101	(2,6)	384	(6,5)	397	(6,8)	**-13**	(5,6)
Brazil	390	(2,8)	89	(1,9)	395	(3,2)	386	(2,9)	**9**	(2,3)
Chile	438	(4,3)	92	(1,8)	448	(5,4)	426	(4,4)	**22**	(4,8)
Colombia	388	(3,4)	85	(1,8)	393	(4,1)	384	(4,1)	9	(4,6)
Mexico	410	(2,7)	81	(1,5)	413	(3,2)	406	(2,6)	**7**	(2,2)
Uruguay	428	(2,7)	94	(1,8)	427	(4,0)	430	(2,7)	-3	(4,0)

Note: Values that are statistically significant are indicated in bold.
Source: OECD PISA 2006 table 2.1.c

Table 5.5

Mean score, variation and gender differences in student performance on the reading scale

	All students				**Gender differences**					
	Mean score		**Standard deviation**		**Males**		**Females**		**Difference (M - F)**	
	Mean	S.E.	S.D.	S.E.	Mean score	S.E.	Mean score	S.E.	Score dif.	S.E.
Argentina	374	(7,2)	124	(3,7)	345	(8,3)	399	(7,4)	**-54**	(7,3)
Brazil	393	(3,7)	102	(3,4)	376	(4,3)	408	(3,7)	**-32**	(3,0)
Chile	442	(5,0)	103	(2,5)	434	(6,0)	451	(5,4)	**-17**	(5,7)
Colombia	385	(5,1)	108	(2,4)	375	(5,6)	394	(5,6)	**-19**	(5,3)
Mexico	410	(3,1)	96	(2,3)	393	(3,5)	427	(3,0)	**-34**	(2,5)
Uruguay	413	(3,4)	121	(2,0)	389	(4,4)	435	(3,8)	**-45**	(4,9)

Note: Values that are statistically significant are indicated in bold
Source: OECD PISA 2006 table 6.1.c

Table 5.6

Mean score, variation and gender differences in student performance on the mathematics scale

	All students				Gender differences					
	Mean score		Standard deviation		Males		Females		Difference (M - F)	
	Mean	S.E.	S.D.	S.E.	Mean score	S.E.	Mean score	S.E.	Score dif.	S.E.
Argentina	381	(6,2)	101	(3,5)	388	(6,5)	375	(7,2)	**13**	(5,6)
Brazil	370	(2,9)	92	(2,7)	380	(3,4)	361	(3,0)	**19**	(2,8)
Chile	411	(4,6)	87	(2,2)	424	(5,5)	396	(4,7)	**28**	(4,8)
Colombia	370	(3,8)	88	(2,5)	382	(4,1)	360	(5,0)	**22**	(4,6)
Mexico	406	(2,9)	85	(2,2)	410	(3,4)	401	(3,1)	**9**	(2,6)
Uruguay	427	(2,6)	99	(1,8)	433	(3,6)	420	(3,1)	**13**	(4,2)

Note: Values that are statistically significant are indicated in bold
Source: OECD PISA 2006 table 6.2.c

This pattern of gender differences is both surprising and expected, given some of the characteristics of the country. On one hand, it is surprising that PISA scores show that Chile has the largest differences between males and females in math and science, and the smallest in language within Latin America, while Chilean national standardized tests show a much more typical pattern of differences, with clear and significant advantages for females in language and disadvantages, albeit not as large as those found in PISA, in math and science. However, our national tests are not comparable with PISA assessments, and neither are they comparable to any other tests administered in Latin American countries. Therefore, this is the only measure we have that allows us to compare our gender differences to those of other countries. And it is important to mention that, even though results in national tests administered at the secondary level show gender differences that may not seem out of the ordinary, there is other additional evidence of gender inequity in these assessments. For example, women's scores in college admissions tests in Chile tend to underpredict their later college performance, while male's scores tend to overpredict theirs (Ortega, 2007). To put it in a different way, given their later performance in college, females should score higher in the PSU than they actually do, and males should score lower. This is consistent with findings from other countries with regards to the relation between college admissions tests and college performance (Zwick, 2006).

On the other hand, gender inequities in test performance in Chile are not completely surprising, given that our country shows other indicators of gender inequity in other areas as well. The 2007 Globar Gender Gap Report (Hausmann, Tyson & Zahidi, 2007) places Chile as one of the Latin-American countries with more inequalities in the global index and in several subindexes. This is shown in table 5.7. As shown in the table, of the six Lati-American countries participating in PISA 2006, Chile is second only to Mexico in the global gender gap index and economic participation and opportunity subindex, and second only to Brazil in the educational attainment subindex (which is not based on tests scores, but on enrollment and literacy rates).

Table 5.7

Rankings in the 2007 Global Gender Gap Index and Sub-Indexes for Latin-American countries participating in PISA 2006. Higher scores represent more inequality.

	Global Index	Economic Participation and Opportunity	Educational Attainment	Health and Survival	Political Empowerment
Argentina	33	75	33	1	25
Brazil	74	62	84	1	96
Chile	86	105	78	1	58
Colombia	24	35	16	1	33
Mexico	93	109	49	1	57
Uruguay	78	66	53	1	115

6. Conclusions and Policy Implications

Chile is a country with a dense network of educational measures that include census and sample data of student achievement, as well as teachers and school level evaluations. The country has also participated in all major international educational assessments at least once. This report has connected these measures and analyzed their data, identifying socioeconomic and school factors that are related to the performance of students. Overall the most basic observation is the impressive relevance of socioeconomic factor in the Chilean educational system. The participation of Chile in PISA 2000 and 2006 allows us to place this observation in the international context. Among all participating countries in 2000 and 2006, Chile appears as one of the countries where most of the between school variance is explained by individual and school socioeconomic factors. In fact, it is the socioeconomic composition of the schools the most relevant factor that consistently shows in international (PISA) and national data (SIMCE and PSU). This observation reveals the degree of social segregation in the Chilean school system that produces strong compositional effects. In fact, when socioeconomic factors are included in the analyses, differences in performance among private, private with subsidy or public schools disappear or even reverse. Of course this is a statistical result, because in practice the social segregation of schools consistently reveals a strong achievement gap between public and private schools. Although most of these socioeconomic factors are beyond the focus of educational policies, there are some measures that should help to ameliorate its role in the case of Chile. The national discussion about educational policies that emerged from the students demonstrations in 2006, has opened the field for discussing some issues that could reduce the role of socioeconomic factors. One key issue is the redesign of the voucher system, which so far has awarded the same amount of resources to all schools, regardless of the socioeconomic composition of their students. A new funding scheme has been recently approved (preferential subsidy, "subvención preferencial"), that should be the first of compensatory policies for the Chilean school system. In addition to funding, new rules regarding the access to schools are also relevant. As shown in this report, student selection is positively related to achievement, eventually accentuating the social gap (because selection is typically performed by schools receiving students from higher socioeconomic families). Preventing selection, at least during the first years of schooling (as recently agreed between the Chilean government and the opposition) should have several positive consequences: reducing the inequality in learning opportunities (poor children do even worse in poor classrooms, than they would do in schools with a more mixed socioeconomical environment), controlling unfair market advantages for selective schools, and making less difficult the task for public schools (because in a selective system, public schools are obligated to receive students rejected by other types of schools).

Another relevant conclusion of this report concerns the role of teachers and teacher evaluation in Chilean educational quality. After many years of educational policies centered on other key aspects of the educational environment (improving educational infrastructure, providing schools with textbooks, libraries and computers, and reforming the curriculum), teachers became the main concern in the last few years. Incentive programs were the first step (SNED and the Certification of Teaching Excellence), followed by the creation of a national teacher evaluation program (for teachers working in public schools). A year ago a new law was passed that requires a mandatory certification of teachers training programs. A new teacher professional development program is still pending. In this context, the results of the analysis involving data from the teacher evaluation program are encouraging, because they show that after controlling for socioeconomic and other school context variables, the score on the teacher evaluation is positively correlated with student achievement as measured by the SIMCE. The analyses provide specific support for the portfolio and peer interview aspects of the evaluation. Based on these results, we consider that the Chilean approach to this evaluation has several positive aspects that could be considered for other contexts: first, it shows that teacher evaluations based on performance standards are not necessarily disconnected from student learning as some critics mention. Second, because the evaluation is reported in specific terms aligned with the standards, it provides explicit and valuable feedback for teachers, offering them precise information about their relative strengths and weaknesses. This is a key difference from student-based teacher evaluation schemes (like those based on value added models), because although the latter do identify effective teachers, they do not offer information on how and why those teachers are more effective. Third, the constructive and not threatening nature of the evaluation, has reduced the resistance of teachers to the evaluation and has promoted a positive use of the results of the evaluation. Fourth, the use of direct evidence about teaching, planning and student evaluation through the portfolio, provides explicit clues about the expected professional behaviors of teachers. Finally, the interview by a peer, which is a particular feature of this evaluation, shows a consistent positive correlation with student performance, suggesting that it is possible to train[15] external evaluators to identify effective teachers. It is also relevant to mention that the supervisor rating was not correlated with student performance. This last result opens many questions about the way school principals understand their role. Instead of being academic leaders, engaged in helping their

15 Peer evaluators participate in a two day training seminar that offers them guidance on how to conduct the interview, and evaluate the teachers they interview.

teachers to improve teaching, most principals in Chile focus only on administrative matters and very rarely take time to observe classrooms and teaching. Therefore, it is not surprising that their ratings of teachers are not connected with the actual behavior of teachers (as revealed by the portfolio) or the performance of students (as revealed in external evaluations). In consequence there is a clear indication that the role of principals has to be addressed, as they, like the teachers, are essential actor of school improvement.

Another interesting result from our analysis is about the perception that parents have regarding the school engagement in analyzing and using available information from external evaluations. This perception, as reported in the SNED evaluation, has a consistent, small, but significant effect on school performance. It is difficult to isolate whether this effect is due to self-selection of parents, or it is an actual effect of information management. If schools monitor their SIMCE scores and use them as an instrument to pinpoint weaknesses and develop strategies, it may well have an effect on their performance. We consider that this particular piece of information opens many questions regarding the actual use of external evaluation data on school improvement, through management and teachers decisions, as well as through the actions of parents (for example, by selecting schools that are more effective). Prior research in Chile indicates that most educational actors do not consider evaluation data for their decisions. Therefore, more research is needed about the specific conditions that lead to the use of this data, as well as about the most effective strategies for translating evaluation results into school improvement.

Finally, this reports also included an analyses about the quality of life consequences of skills developed through education. Using data from the adult sample (aged 15 to 65) that participated in the 1998 International Adult Literacy Test, we found significant positive effects of literacy skills on labor participation and the access to responsibility positions in job. We also found significant negative effects of literacy skills on poverty condition. Additionally, a greater literacy skill level is associated with higher earnings, once schooling and other earnings related variables are taken into account, especially for people with less than higher education. These results suggest a dynamic relationship between the development and the use of literacy skills at work: less educated workers enter jobs that do not require the use of literacy skills (which in turn explains the decline in those skills of that group over time). As schooling increases, the initial skill level also grows and its use in work also increases throughout the work cycle. Moreover, higher literacy ability is linked to higher incomes for low-trained workers. Among better educated workers, literacy ability has no effect on earnings, apart from the already internalized higher educational attainments that this would imply. Altogether, this section of the report offers very relevant information about the specific pattern of relationships between educational outcomes and quality of life.

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