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Inequality of Learning Opportunities in Chile: Measures and Recent Trends[♣]

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Abstract: Despite all the changes made in the Chilean education system in the past decades, the overall progress in students' learning has been unsatisfactory. In addition, stratification probably increased over this period. Since inequality in education opportunities might be one of the main channels of intergenerational transmission of economic inequality, this paper focus on providing measures and an analysis of the evolution of the opportunity share of inequality in educational achievements in Chile. Using data from SIMCE and PISA surveys in 2001 and 2006, it is shown that a lower bound of 16% to 29% of the observed inequality can be explained by uneven circumstances. Moreover, we find evidence of a slight decrease in the share of inequality of learning opportunities in Chile between 2001 and 2006. Contrarily common observations in other contexts, family income and father's occupation are the strongest correlates of inequalities in achievements, among various socially inherited circumstances, with parental education coming only second. Finally, when controlling for family background and geography, enrollment in a public or private school remains associated with a large share of learning inequalities.

Keywords: Educational achievement, Inequality of Opportunities, Chile.

JEL Codes: D39, D63, I29

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1. INTRODUCTION

The Chilean education system has gone through several reforms during the past decades. Most changes sought to introduce more competition and explore market mechanisms to increase enrollments as well as to improve the quality of the education provided. The reforms, initiated in 1981, have consisted mainly in a vouchers financing scheme allowing students to study in the schools of their choice as long as the school had entered in the voucher system. As a result, the share of enrollment in private schools has subsequently increased. Seeking to evaluate the performance of schools and to inform family choices, Chile has also been a pioneer in the collection of data on students' achievements. The data from the "Sistema de Medición de la Calidad de la Educación" (SIMCE) have been collected on a regular basis since the 1980s.

These innovative policies have attracted much attention and their impacts remain in debate. The first question addressed by the literature asks whether the quality of the education provided has been enhanced by the reforms. A number of studies have in particular examined the respective performances of public and private schools. No consensus seems to have been reached on this point (McEwan, Urquiola and Vegas, 2008). While several authors have found that subsidized and unsubsidized private schools seem to enhance students' achievements (Auguste and Valenzuela, 2000; Gallego, 2006; Anand, Mizala and Repetto, 2008), a number of studies present evidence of very small or no difference in test scores across school types (Mizala and Romaguera, 2000; Hiesh and Urquiola, 2003; Bellei, 2007). Reviewing this literature, Bellei (2007) argues that the results discussed in the literature are extremely sensitive to the methodological decisions made by the authors to identify the specific effect of schools' types, and that the lack of an experimental evaluation of the Chilean case makes it difficult to reach a consensus.

The second question addressed in the literature wonders whether the sorting of children from different family background into different schools increased with the reforms and how did these changes impact Chilean children's learning outcomes. The questions on stratification are closely related to the one on quality for two reasons. First, increased stratification could induce social interactions, and externalities, that could lower the achievements of some students and the aggregate learning outcomes of Chilean children. Second, the performances of schools are not easily distinguished from the family resources of children, and the observed differentiation between schools could in fact come from an increased stratification. The sorting of children between different schools could be driving the positive effects of private schools on achievements observed in some studies.

There seems to be more evidence regarding the stratification of children from different socio-economic origins across schools than on the effects on quality. For instance, Hsieh and Urquiola (2006) study a panel of 150 municipalities in Chile from 1982 to 1996 and, exploiting some exogenous variations in the access to private schools, find that the sorting of children from different socio-economic origins did increase after the implementation of the voucher system. In the meantime, they find no evidence of improvement in aggregate educational achievements. Considering the implications of sorting for the evaluation of schools' performance, Mizala, Romaguera and Urquiola (2007) observe that a ranking of schools according to average students' achievements is strongly correlated with a ranking according to students' socio-economic status, and hence cannot be used as a clear signal about schools' quality.

This brief discussion makes clear that large scale reforms such as those introduced by Chile should affect both the average and the distribution of achievements of children, and that both dimensions need to be taken into account in policy analysis.

This paper aims to take a broader look at the changes in the distribution of learning outcomes by adopting the perspective of inequality of opportunities. Recent studies have sought to derive measures of inequality for the distribution of economic but also educational opportunity (see Van de Gaer, Schokkaert and Martinez, 2001; Bourguignon, Ferreira and Menendez, 2007; Checchi and Peragine, 2005; Ferreira and Gignoux, 2008). Most of the proposed measures have relied heavily on the theoretical framework proposed by Roemer (1998). They all consist in relating the distribution of given outcomes, such as labour market earnings, to observed morally irrelevant circumstances, by using the information on variables such as ethnicity, parental occupation and education, or place of birth[1]. Although most of the literature concerns economic outcomes and a few studies educational attainments, Ferreira and Gignoux (2007) show that this approach applies, with a few adjustments, to the study of learning achievements.

This paper applies this approach to study the levels of inequality in learning achievements associated with a set of circumstances and their recent changes between 2001 and 2006. The equality of opportunity perspective seems particularly relevant for studying learning outcomes. Although family and local resources should be strong determinants of learning opportunities - either directly through home investments in children learning or indirectly through access to good quality schools -, individuals' abilities and efforts remain important determinants of learning outcomes. Therefore the inequality of opportunity approach can help capture the changes over time in the weight

[1] Although these studies are related to the literature on intergenerational mobility, differences exist. First, the set of circumstances is broadened beyond family background to include variables such as gender, ethnicity, or geography. Second, the focus is put on the overall effect of a set of pre-determined circumstances. Torche (2005) provides some evidence on changes in intergenerational educational mobility in Chile. Using a cohort analysis, she finds much persistence in intergenerational correlation of school attainments, even for the generations that were directly affected by most of the reforms.

of circumstances exogenous to individuals' behaviours, such as features of the educational system, and hence provide some insight into the distributional outcomes of the reforms. It can be viewed as a reduced form analysis of the distributional effects of policies. For instance, changes in the sorting of children from different backgrounds into schools should be an important factor of changes in inequality of learning opportunities. However, the changes in the quality of education provided by schools will also be taken into account in the analysis of this sort of inequality.

This study also seeks to contribute to the debate on the importance of data on achievements. Such data have been used to monitor the changes in the average achievements of Chilean children as well as to evaluate the performances of individual schools and inform families. Some critics have recently been formulated on the relevancy of these data to effectively evaluate and rank schools, given the difficulty first to correct for sorting of children with different backgrounds into schools, and second to control for usual fluctuations in students' abilities across time and schools (Chay, McEwan, Urquiola, 2005). Here, we show that such data can be useful to provide aggregate measures of the distributional outcomes of education policies.

The following analysis is based on two different sources: the OECD surveys Programme for International Students' Assessment (PISA) of 15 year-olds, conducted in a sample of schools in 2001 and 2006, and the Chilean Ministry of Education's SIMCE surveys, censuses of children attending the second grade of the secondary level, that were also conducted in 2001 and 2006. Nonparametric and parametric estimates allow computing the shares of the overall inequality in test scores associated with a set of circumstances variables, namely gender, parental education, occupation, and income, school location, school type and ethnicity. The type of schools attended, i.e. subsidized, not subsidized and public schools, is included in the set of circumstances in order to shed light on the share of inequality associated with school choice.

The results suggest that unequal opportunities account for 16% to 29% of the variation in test scores among Chilean children studying at the secondary level. In addition, family background is associated with the largest share of unequal opportunities. For instance, parental income seems to account for up to 10% of the overall inequality. The comparison of the results for 2001 and 2006 suggests that the share of opportunity in the overall inequality decreased over time, which could be possibly connected to the recent fall in income inequality observed in the country.

This paper is organized in five sections. Following this introduction, the next section describes the data sets used in the analysis as well as compares them and discusses their limitations. The third section presents the methods implemented here and the fourth section examines the main results. The last section concludes.

2. DATA

Together with all transformations in the education system in Chile, average achievements per school have been made public since mid-nineties to guide parents in choosing the school to enroll their children (McEwan, Urquiola and Vegas, 2008). In fact, students' scores have traditionally been used in Chile to measure account for educational achievements achievement and have been included in several analyses of the education system, starting at the end of the eighties.

Educational achievements are usefull to monitor schools' performance, but are also considered as better measures of individual's educational experience than mere attainment, and standardized test score are generally preferred to complete years of schooling to capture achievement.

This paper uses data from the two main sources of information on educational achievements in Chile for the years of 2001 and 2006. The first one is SIMCE (*Sistema de Medición de la Calidad de la Educación*), which is a cross-section survey conducted by the Chilean Ministry of Education, including students in 4th and 8th grades of primary school, as well as students in the second grade of secondary level. In order to keep comparability with the second data source, only the SIMCE surveys conducted in 2001 and 2006 for students in the secondary level were included in the analysis presented in the next sections. The samples at the secondary level contain 192,945 observations in 2001 and 225,078 in 2006.

SIMCE gathers information on achievement in Spanish and math and contain information on a number of circumstance variables as well. Among them we can list gender, father's and mother's education, father's occupation, school location (type of area), family income and ethnicity. Unfortunately, father's occupation and ethnicity were collected only in 2006.

The second source of data used in this paper is PISA (Programme for International Student Assessment), which is an internationally standardized assessment in reading, math and science. However, among the exams administrated we consider only the outcomes in reading and math in order to contrast with the results from SIMCE. However, the results of the standardized exams in PISA are provided in plausible values[2]. The

[2] The inference of statistics of unobserved latent variables, such as achievements, gives rise to a measurement error problem. Each individual answers a limited number of items so that it is not possible to

population of interest encompasses all 15 year-olds enrolled in school regardless of grade[3]. The cross-section samples contain 4,889 observations (2721 for math) in 2001 and 5,308 in 2006. It is important to point out that the weighted sample of the PISA 2001 represents 82% of the overall population of 15 year-olds in 2001, whereas the weighted sample of PISA 2006 represents 78% of that population[4], since not all 15-year-olds are. The PISA surveys also include information about a number of circumstance variables: gender, parents' education, father's occupation and school location (type of area). A summary of the characteristics of each survey, including the number of observations, populations of interest and the circumstance variables, can be found in table 1.

In each survey the sample was partitioned on the basis of the observed circumstance variables. Table 2 describes the circumstance variables, along with mean test-scores, for both surveys and years. With the exception of ethnicity and gender, all circumstances variables were coded using three categories. This parsimony is made necessary by the limited sample sizes of the PISA surveys. Some remarkable points can be taken from table 2. First of all, the majority of the students considered here have parents with complete or incomplete secondary level in both surveys, while another high percentage has parents with even lower education (around 30%). Also, most of them are concentrated in urban areas (55.4 % in 2001 and 57.2% in 2006 according to PISA), and although the majority of the students were in public schools in 2001 (55% in PISA and 47.6% in SIMCE), the distribution across school types has changed over time. In fact, in 2006 the share of students in public or not subsidized private schools has decreased, increasing the proportion of students in subsidized schools.

It is important to keep in mind that the categorization used for the PISA and SIMCE data differ slightly, despite all the effort in making the two data sets as comparable as possible. This piece of information can partially explain the differences observed in table 2. Besides, some of the results in table 2 suggest a sampling issue with the PISA survey. Although there is a clear difference in the categorization of the circumstance variables and in the population of interest between the two surveys used here, given that the rates of repetition in Chile are not so high (table 3), one should not expect the PISA survey to differ much from the SIMCE data, which is a census. In addition, the population surveyed by the PISA in 2001 and 2006 are not perfectly identical; in particular, the

estimate individual achievements accurately. In this situation, the distribution of estimates for individual achievements obtained with traditional methods, such as maximum likelihood estimates, does not converge to the population distribution of these achievements as the number of examinees increases (Mislevy et al. 1992). These estimates are thus inconsistent. Plausible values are a standard solution for this measurement error problem. These are multiple imputations of the unobserved latent characteristics, achievement here, for each student. For more details see Mislevy (1991) and Wu (2005).

[3] Children enrolled in grade 6 or lower were excluded from the sample, but these are very few in Chile.

[4] The population of 15 year-olds was estimated at 263,863 in 2001 (OECD 2001) and 299,426 in 2006 (OECD 2007).

population encompasses 47% of boys in 2001 but 54% in 2006. There is no clear explanation for these differences but they certainly raise some concerns on the PISA sampling.

Another caveat in working with these datasets is that the populations surveyed by PISA and SIMCE are not representative of the overall population of children. As mentioned above, the PISA surveys collect information on a sample of 15 year-olds attending school, despite the actual grade they are attending, whereas SIMCE survey collect information among children attending the second grade at the secondary level[5].

The selection of the surveyed population raises two concerns. First, the estimates of inequality of opportunity are potentially biased because drop-outs are not taken into account, and dropping out is likely to be correlated with circumstances. The estimates could encompass a selection bias due to dropping out. However, this selection bias may be limited in the case of Chile because most 15-year-olds are enrolled. Table 3 gives enrollment rates at primary and secondary levels between 1999 and 2005. The enrollment rates are high, close to 90 percent, at the secondary levels.

Second, a selection of the population based on age is not the same as one based on the attained grade. Children attending the same level might have different ages because of grade repetition. When analyzing SIMCE data it is important to bear in mind that we are comparing the achievements of children at various ages. This could lead to an additional selection bias due to grade repetition. This problem does not concern the PISA data, and the measures of inequalities in achievement at a given age obtained with these data are thus more satisfactory in this sense than the measures at a given grade obtained with the SIMCE data.

The SIMCE survey collected information on repetition. In 2006, at the second grade of the secondary level, the proportion of student having repeated one grade is 15.1 percent, and the proportion having repeated two or more grades is 3.9 percent among (although 17 percent of students did not answer the question)[6]. We do not address these selection problems in this paper. Therefore, the results presented in section 4 should be interpreted with this caveat in mind.

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[5] The age of a student attending the second grade of the secondary level, and not having previously repeated a grade, is also 15 years old.

[6] Table 3 also provides mean repetition grades at the end of each grade at the primary and at the secondary levels. These rates are close to 2.5 percent. Assuming every child enters school at the appropriate age of 6, and no drop-out, the cumulative of repetition implies that on 8 percent of children have repeated a grade at the fourth grade of the primary level, and about 25 percent of children at the second grade of the secondary level. These figures go down if some children repeat two or more grades. These statistics are thus in line with the SIMCE data.

3. METHODS

The main goal of this paper is to examine the evolution of inequality of opportunity in educational achievements over time, and to study the partial shares of overall inequality associated with different circumstance variables. In order to do so, we use a similar framework as the one proposed by Ferreira and Gignoux (2008), which aimed to compute a lower bound for the share of overall inequality associated with uneven opportunities. Although there is an extensive theoretical literature exploring the concept of inequality of opportunity, methods to quantify it have only recently been developed. In fact, there is still no systematic measure of inequality of opportunity. Ferreira and Gignoux (2008) discuss and organize in a uniform framework a class of alternative, but closely related, measures.

According to the authors, one can think about the outcome of interest, in this case educational achievements, as a function of efforts and circumstances. Efforts, in John Roemer's jargon, represent all variables that an individual can choose given the circumstances that he or she faces. Therefore, one can define the following structural model:

$$\begin{aligned} y_i &= f(C_i, E_i, u_i) \\ E_i &= g(C_i, v_i) \end{aligned} \qquad (1)$$

where y_i represents the test score in a given test and C_i and E_i are vectors of circumstances and effort variables for individual i, respectively. The error terms are represented by u_i and v_i, which include the effects of mere luck, and $g(.)$ stands for a set of equations, one for each effort variable.

With this framework in mind, one can try to decompose the total inequality in achievements into an amount due to uneven opportunities and a residual term. The resulting share associated with inequality of opportunities will be of the form:

$$\theta(\{\tilde{y}\}) = \frac{I(\{\tilde{y}\})}{I(\{y\})} \qquad (2)$$

where *I(.)* stands for some inequality index, $\{y\}$ represents the original distribution of educational achievements, while $\{\tilde{y}\}$ is a counter factual distribution which is obtained from the original one by eliminating all inequality among students that share identical circumstances. In this case, $I(\{\tilde{y}\})$ will be a measure of the inequality associated with different circumstances.

All measures of the opportunity share presented here are variants of this basic idea. The first two methods follow Checchi and Peragine (2005), who develop non-parametric approaches, each of which is based on different, yet equivalent, definitions of inequality of opportunity. Their first approach departures from the idea that there is equality of opportunity if and only if the expected value of the outcome of interest is the same regardless of the circumstances. Following this definition, they proposed the construction of a *smoothed distribution* $\{\mu_i^k\}$, where the observed outcome of interest of each individual is replaced by the mean outcome of all individuals with the same circumstances set. This means that for a given partition $\{y_i^k\}$, where all $i \in k$ faces the same set of circumstances, y_i^k will be replaced by μ^k, which is the mean of the outcome for this specific partition. The inequality existent in this counterfactual distribution would be entirely due to unequal opportunities and the resulting opportunity share of the overall inequality is set by

$$\theta_d^N = I(\{\mu_i^k\})/I(\{y_i^k\}), \tag{3}$$

for a given measure of inequality $I(.)$. θ_d^N is therefore a non-parametric method of directly measures between-group inequality, hence the subscript *d*.

Their second approach is based on the following definition: "there is Equality of Opportunity if and only if all those who exerted the same degree of effort have the same chances of achieving the objective, regardless of the type." This approach will give emphasis to inequalities within effort groups, rather than between groups. They suggested the construction of a different counterfactual distribution $\{v_i^k\}$, where the mean of the overall distribution is preserved within each circumstance partition. This new distribution was called *standardized distribution* by the authors, which is built by substituting each individual's outcome by his outcome times the ratio between the overall mean and the mean of his group-specific mean. For a given partition $\{y_i^k\}$, where all $i \in k$ face the same set of circumstances, y_i^k will be replaced by $y_i^k(\mu/\mu_i^k)$, where μ is the overall distribution mean. The inequality that remains in this counterfactual distribution is associated to unequal efforts, and the consequent share of overall inequality associated with inequality of opportunity is

$$\theta_r^N = 1 - I(\{v_i^k\})/I(\{y_i^k\}), \tag{4}$$

which measures the between-group inequality by extracting the residual term of the overall inequality after subtracting the within-group inequality, hence the subscript *r*.

Although both methods discussed above are clearly equivalent, they do not necessarily lead to the same measure of inequality of opportunity. In order to achieve the same result through these alternative approaches, it would be necessary to use an inequality index that is not path-dependent, as for example the mean log deviation index (Foster and Shneyerov, 2000; and Ferreira and Gignoux, 2008). Another caveat of these methods is that they are heavily dependent on large data sets to minimize the number of partitions $\{y_i^k\}$ with none or very few observations. In particular, when the sample sizes are limited (such as for the PISA surveys), the non-parametric measures can overestimate the between-group inequality because of large sampling variance in small sample cells.

An alternative approach, which can be used to deal with the small sample cell issue, was proposed by Bourguignon, Ferreira and Menendez (2007). According to the authors one can also construct a parametrically standardized distribution $\{\tilde{y}_i\}$ by estimating a reduced form model of the effects of circumstances on achievement and replacing y_i with $\tilde{y}_i = f(\overline{C}, g(\overline{C}, v_i), u_i)$, where the upper bar on the vector C denotes sample mean circumstances. With the simulated income distribution it is possible to extract how much of inequality is due to inequality of opportunity by comparing the simulated and the actual distributions. Similarly to the second approach proposed by Checchi and Peragine (2005), the inequality observed in the counterfactual distribution should be related to different levels of effort, and the suggested measure of inequality of opportunity in this case is

$$\theta_r^P = 1 - I\left(\{\tilde{y}_i^k\}\right) / I\left(\{y_i^k\}\right). \qquad (5)$$

The parametric approach, at the price of loosing the flexibility in the functional form, which is assumed here to be linear, has the additional advantage of permitting the estimation of the partial share of inequality associated with one (or a subset) of the circumstance variables on overall inequality. This is calculated by constructing the alternative counterfactual distribution $\hat{\tilde{y}}_i^J = \overline{C}_i^J \hat{\psi}^J + C_i^{j \neq J} \psi^{j \neq J} + \hat{u}_i$, and computing the circumstance J-specific inequality share as:

$$\theta_r^J = 1 - I\left(\{\tilde{y}_i^J\}\right) / I\left(\{y_i^k\}\right). \qquad (6)$$

However, it is important to bear in mind that the interpretation of these partial shares in terms of effects requires an additional assumption: any omitted circumstance variables in this model must be orthogonal to the observed ones. This was not needed to estimate the lower bound of the overall opportunity share, yet it is needed for estimating partial effects.

A specific problem must be addressed for measuring inequality of opportunity using data on achievements: one must deal with the standardization of test scores variables. There is no scale of absolute levels of achievement so that the test-scores provided by each survey are obtained after the imposition of arbitrary scales for both the mean and the dispersion[7]. Zheng (1994) shows that there is no usual inequality index that can satisfy both properties of translation and scale invariance. Thus the arbitrary imposition of a scale, with both a reference and a unit value, makes it impossible to compute the *levels* of overall inequality in achievements. However, Ferreira and Gignoux (2007) show that some scale independent measures of the *shares* of inequality of opportunity over total inequality do exist. Specifically, the solution consists in using E(2), the squared coefficient of variation, for the measure of inequality $I(.)$ in equations (3)-(6). The obtained shares of overall inequality associated with unequal opportunities are independent from the arbitrary choice of scales.

4. RESULTS

Before discussing the measures of the opportunity share of inequality in achievements, we present in tables 4A, 4B, 5A and 5B the regressions used for the parametric decompositions. The results for SIMCE are displayed in tables 4A and 4B and for PISA in tables 5A and 5B. In tables 4A and 5A all the observed circumstance variables were included, with the exception of school type[8]. Almost all coefficients are significant at the 5% significance level for the PISA[9], and they have the expected signs using data from both surveys. In particular, mother's education as well as father's occupation and family income seem to be the main correlates of students' scores, as large variations of achievements are observed between children of mothers with different levels of schooling or household with different economic status.

Tables 5A and 5B add school type to the previous set of circumstance variables. The results are similar to the ones presented in tables 4A and 4B. The main difficulty in interpreting the coefficients associated with school type is that, because many families choose the type of school where they enroll their children, it might be correlated with omitted characteristics of children and families. Some of these characteristics would be considered as circumstances while others may not[10].

[7] For instance, the test-scores from PISA are such that, for the population of 15 year-olds in OECD countries in 2000, the distribution of test-scores has a mean of 500 and a standard deviation of 100.
[8] Also ethnicity and father's occupation were not included in the regressions using the 2006 SIMCE data.
[9] The SIMCE is a census so that there is no sampling variation, so that no attention is devoted to the estimated standard errors.
[10] The existence of omitted circumstance variables that are correlated with the observed ones do not invalidate the decomposition proposed in the previous section. However, the analysis of partial effect should be done carefully, since it requires observed and non-observed variables to be orthogonal among them.

It is well known that private schools are more rigorous in accepting students. For instance, in 2005 about 62% of the unsubsidized private schools would require children to take an entrance exam before admitting them, while only 7.6% of public would use this practice. Among subsidized private schools about 43% required entrance exams (McEvan, Urquiola and Vegas, 2008). Therefore, it is possible that private schools do not only provide better quality in education, an issue that is still in debate in the literature, but also that they gather better students. This means that the *dummy* variables for private schools might capture the direct effect of better education, as well as the average higher ability of the students. Also, it might be possible that parents who are more concerned about their children's education would enroll them in private rather than in public schools, given the belief that private schools offer better quality, meaning that variables for school type might be correlated with parents' preferences as well. Therefore, we need to interpret the results presented here with some caution.

As expected, in all regressions the coefficient of the private school variable is positive and it is even higher for unsubsidized ones. In addition, the effects of the other variables decrease with the inclusion of *dummy* variables for school type, but parent's education as well as father's occupation and family income remain important determinants of students' scores when controlling for school type.

The results for the measures of inequality of opportunity are presented in tables 6 and 7 for the SIMCE and PISA surveys, respectively. For the SIMCE 2006 data, we present an additional set of results obtained by adding ethnicity and father's occupation to the initial set of circumstance variables. The first rows of tables 6 and 7 give the results for the share of inequality associated with the entire set of circumstance variables. The second rows present the non parametric smoothed indices, while the third rows show the non parametric and the fourth rows the parametric standardized indices. The following rows display the partial shares of inequality associated with individual circumstance variables. Unequal opportunities account for a lower bound of between 16% and 26% of the variation in test scores among Chilean children according to the parametric estimates using the SIMCE survey and between 19% and 29% using the PISA data.

The estimated bounds on the shares of inequality of opportunity tend to be higher with the data from PISA than with the data from SIMCE. The sample designs are the main difference between the two surveys, and this could possibly explain these differences. As mentioned above, while PISA surveyed all 15 year-olds, SIMCE surveyed all children attending the second grade of secondary school. Since it is expected that 15 year-olds will be attaining this specific grade, the difference between the two samples comes from children who repeated grades. While repeaters are surveyed at 15 years old by PISA, they are surveyed at an older age, once they have reached the second grade of secondary schooling, by SIMCE. Moreover repetition is probably associated with specific circumstances. Therefore, the between group inequality should be lower when SIMCE sample is used. Another difference that was highlighted in table 1 lies in the lower share of children attending private schools in PISA than in SIMCE. This suggests that private schools are underrepresented in the PISA sample. This could also explain the differences in the estimates of inequality of opportunity between the two surveys.

Figure 1 contrasts the opportunity shares of inequality in achievements in 2001 and 2006. The opportunity share of inequality in achievements seems to fall over time. In particular, the estimates for SIMCE exhibit a decline between 2001 and 2006 comprised between 0.9 and 1.4 points in Spanish and between 3.7 and 7.5 points in Mathematics. The variations of the estimates for PISA are not statistically significant, which can be explained by the small sample sizes. Overall, these results suggest a slight decline of the opportunity share of learning inequalities during recent years.

One might wonder how Chile compares with other countries in regards to inequality of opportunity in achievements. The PISA surveys were implemented in a large number of countries, mainly OECD countries but also countries from Latin America, the Middle East and Asia, and allow for cross country comparisons. Using these data, Ferreira and Gignoux (2007) find close estimates of the share of overall inequality associated with uneven opportunities - lying between 0.17 and 0.21 and not significantly different - in other Latin American countries, including Argentina, Brazil, Mexico, and Uruguay. Larger variations are found among countries with level of development comparable to Chile's in other regions; for instance, the same estimates are close to 0.14 for Turkey and 0.12 for Tunisia. Thus, Chile does not set apart from other Latin American in regards to those measures of inequality of opportunity in achievements.

The partial shares of inequality associated with individual circumstance variables are exhibited in figure 2 and 3, and reported in tables 6 and 7. When school type is not included, family background variables are the most important, in particular mother's education (associated with 7-9% and 9-13% of total inequality with SIMCE and PISA data, respectively), father's occupation (7-11% with PISA), and family income (6-14% with SIMCE). Moreover, the bulk of the inequality associated with father's occupation in SIMCE decreases considerably when parental income is added in the analysis (see columns 6 and 12 on table 7).

An important finding about partial shares is that the inequality associated with income and father's occupation is relatively high when compared with mother's education. Although parental education has been recognized in the literature as one of the main determinants of educational achievement, in a country with an income distribution as unequal as Chile, it is possible that income plays a comparatively more important role in explaining the variation in test scores. School location, gender and ethnicity are all associated with a limited share of the overall inequality in both surveys and years.

When school type is included in the analysis, it becomes the most important circumstance to account for the observed variation in achievements. It seems to explain about 7 to 15 percent of overall inequality in scores in SIMCE and 7 to 11 percent in PISA. Also, by including the information about school type in the analysis, mother's education, father's occupation and parental income loose part of their importance in explaining the variation on students' scores. This result is consistent with the acknowledged strong correlation between the students' socioeconomic status and the type of school they are enrolled (Mizala, Romaguera and Urquiola, 2007). For this analysis of partial shares of inequality, we make an effort to include the larger possible set of circumstance variables, notably in the last specification for the SIMCE 2006. However, as mentioned above, all partial effects have to be considered with caution, since it is expected that a number of omitted variables will be correlated with school type, for instance.

Figures 2 and 3 allow a clear comparison of the shares of inequality associated with individual circumstances between 2001 and 2006. An interesting finding is that, even if they remain important predictors of inequality in achievements, family income and father's occupation seem to loose explanatory power over time. This pattern is observed for both exams using SIMCE, but only for reading in PISA. Although changes in the distribution and effects of unobserved circumstances correlated with income and father's occupation might also play a role, the observed decrease in the shares of inequality associated with these variables might be a result of the recent decrease in economic inequality in Chile[11].

5. CONCLUSION

Education is one of the main channels of intergenerational transmission of inequality. Children with poorer socio-economic status are likely to complete less years of schooling as well as to learn less while in school, partially due to the low access to good quality schools. The lack of proper education is later on translated in lower earnings and welfare. In this paper, we computed and analyzed the share of inequality in educational achievements of secondary level and 15-year-old students associated with a broad set of circumstances, including gender, family background, geography, and school type, in Chile for the years of 2001 and 2006.

[11] According to the results from ECLA 2006, there has been a fall in economic inequality in the last years in Chile.

The results presented here suggest that the opportunity share in inequality of achievements accounts for a lower bound of 16 to 29 percent, depending on the exam and year considered. Moreover, using the SIMCE data, we find evidence of a slight decrease in the share of inequality of learning opportunities in Chile between 2001 and 2006.

This paper also highlighted the role of income or father's occupation in explaining the overall dispersion in test scores. Although parent's education, in particular mother's education, has been traditionally studied as one of the main determinants of children's outcomes, their explanatory powers are just below the ones of income and father's occupation variables. This is likely to be a result of the large income disparity observed in the country vis-à-vis the dispersion in parents' education. The analysis of partial shares suggests that the fall in the opportunity share could be mainly associated with a decline in the explanatory power of income and father's occupation variables. Although this paper did not investigate the reasons for this change, it was speculated here that it can be partially related to the recent reduction in income inequality observed in the country.

The results presented here suggest two main topics for future research. First, the analysis of a longer period of time would allow a better understanding of the trend of the opportunity share[12]. Here we suggested that there is a reduction in inequality of opportunity in educational achievement, based on the analysis of only two points in time, with merely 5 year gap between them. Therefore, it is hard to take any final conclusion about the evolution of the inequality of opportunity in education, which would allow us, for example, to contrast with the findings from Torche (2005), who found evidence of persistent inequality of opportunity in education attainment.

Second, our results suggest a deeper analysis of the PISA sampling design. Despite the differences between the two surveys, several inconsistent facts can be taken from the PISA sample. The distributions of some of the variables considered here seem to diverge between the two surveys, as well as between 2001 and 2006 PISA surveys. Since SIMCE is a census, these differences point to the need of a re-evaluation of the PISA sampling design.

[12] SIMCE data from 1998 are available, including information on family background, for second grade of secondary level students in SIMCE. However, the data does not allow to merge test scores with the information on family background at the individual level.

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Figure 1. Opportunity Share of Inequality in Educational Achievements in 2001 and 2006, SIMCE and PISA

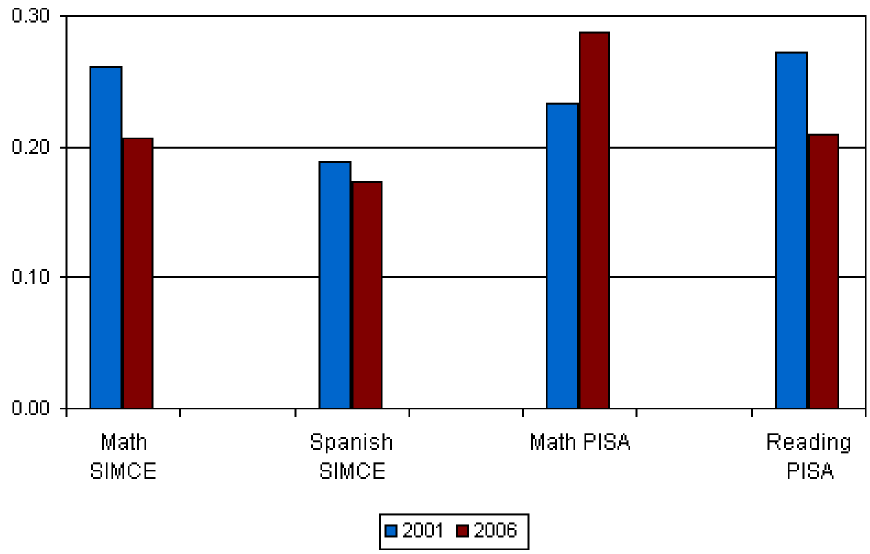

Figure 2. Partial Effects of Each Circumstance on Educational Inequality, PISA

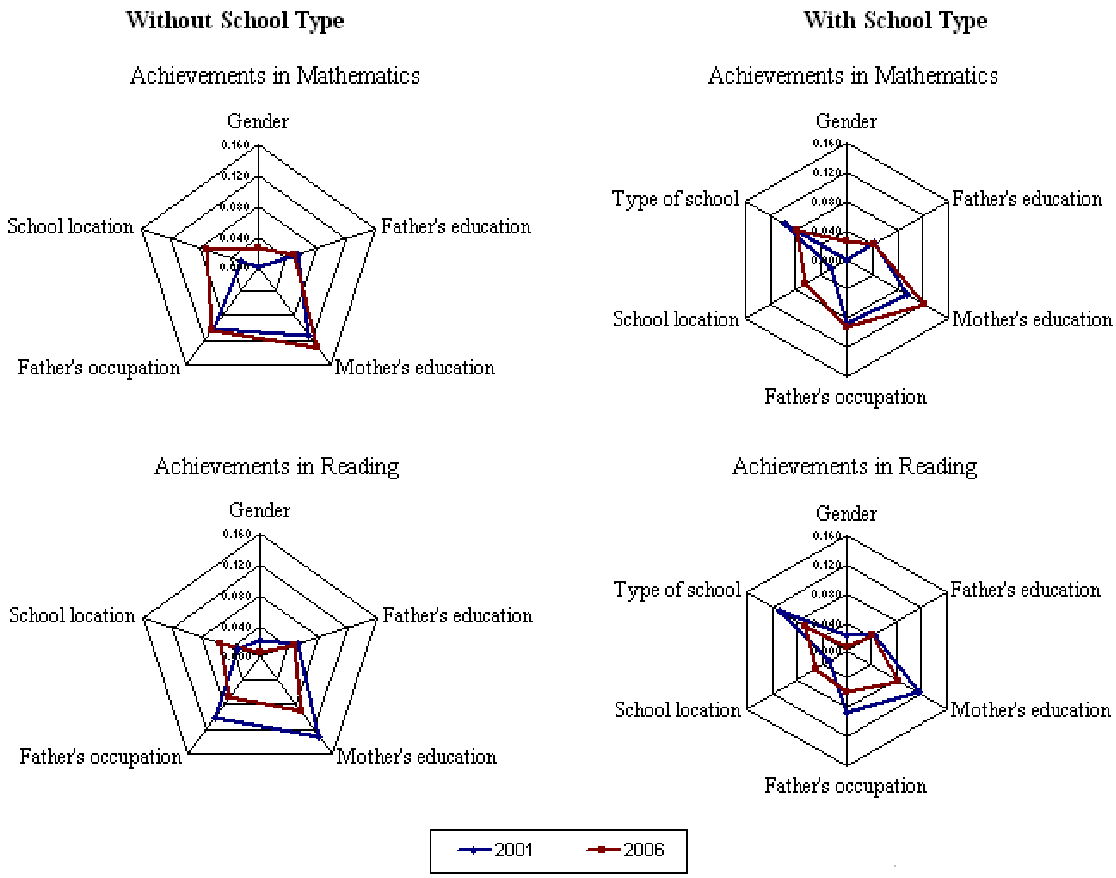

Figure 3. Partial Effects of Each Circumstance on Educational Inequality, SIMCE

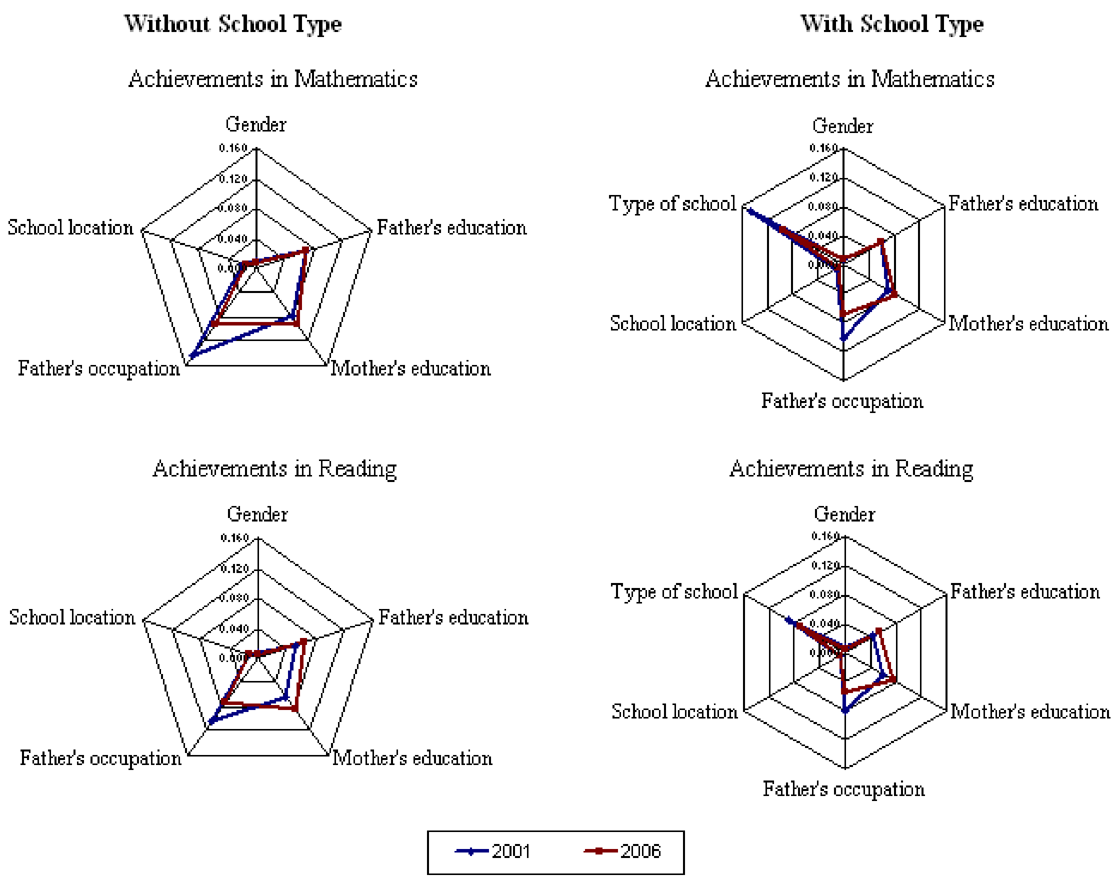

Table 1. Data description: PISA and SIMCE

	SIMCE 2001 2nd grade secondary	SIMCE 2006 2nd grade secondary	PISA 2001	PISA 2006
Samples	192,945 (census)	225,078 (census)	4,889 reading/ 2721 math	5,308
Selection criteria	students of 2nd grade of secondary level	students of 2nd grade of secondary level	15 years olds	15 years olds
Circumstances				
Gender	yes	yes	yes	yes
Parents' education	yes	yes	yes	yes
Father's occupation	no	yes	yes	yes
Parental income	yes	yes	no	no
Ethnicity	no	yes	no	no
School location	yes (region/department)	yes (region/department)	yes (urban/rural)	yes (urban/rural)
Achievement variables	IRT	IRT	IRT, Plausible values	IRT, Plausible values

Table 2. Summary statistics for SIMCE and PISA

	SIMCE*		PISA	
	2001	2006	2001	2006
Gender				
male	49.9	48.3	47.0	54.0
female	50.1	51.7	53.0	46.0
Father's education				
0-8	28.0	23.0	33.7	34.9
9-12	30.1	39.1	41.7	35.0
13+	16.4	21.1	19.6	22.1
unknown	25.5	16.9	5.0	8.0
Mother's education				
0-8	28.0	23.0	33.7	34.9
9-12	32.7	41.4	43.0	37.4
13+	15.2	20.1	14.8	20.3
unknown	20.3	13.7	2.0	3.8
Father's occupation				
Group 1		11.7	22.7	22.9
Group 2		29.4	46.9	48.2
Group 3		35.2	30.4	21.7
unknown		23.7		9.0
School location: type of area				
village or small town (<15,000 inhabitants)			16.6	19.5
town (<100,000 inhabitants)			28.0	23.3
city or metropolis (over 100,000 inhabitants)			55.4	57.2
School location: groupings of departments				
Group 1	40.6	33.5		
Group 2	40.7	34.6		
Group 3	18.6	31.9		
Type of school				
Public	47.6	42.7	55.0	46.9
Private subsidized	42.8	50.2	31.4	44.9
Private not subsidized	9.7	7.1	13.7	8.2
Parental income				
Less than $100 in 2001 (200 in 2006)	24.3	42.0		
Between $100.01 and $400 ($200.01 and 500 in 2006)	48.9	27.4		
$500.001 or more	16.1	16.4		
missing	10.8	14.2		
Ethnicity				
other		74.2		
indigenous		7.0		
missing		18.8		
Mean score in reading	251.3	254.8	415.4	446.1
Mean score in math	246.6	252.7	388.9	415.7
Observations	192945	225679	4884	5308

Notes: The first group of father's occupation is composed by legislators, senior officials, professionals and technicians. The second one inlcudes clercks, service, craft and related trades workers, plant/machine operators and assemblers. The last one is formed by skilled agricultural and fishery workers and elementary occupations. The department were grouped according to students's scores, so that each group includes about one third of the students in the sample. The second group is composed by Arauco, Cachapoal, Cautín Sur, Chiloé, Choapa, Colchagua, Concepción, Curicó, Elqui, Linares Magallanes, Palena-Chaitén, Talca, Valparaíso and Ñuble. The third group is composed by Coihaique, Cordillera, Llanquihue, Osorno, Santiago Centro, Santiago Oriente, Santiago Poniente and Valdivia. The firs group includes all the other departments. A student was coded as indigenous if at least one of the parents were indigenous. *Only secondary level students were included in the SIMCE sample.

Table 3. Enrolment rates at primary and secondary levels, 1999-2005

	Years						
	1999	2000	2001	2002	2003	2004	2005
Gross enrollment ratio[a]							
Primary	100.6	100.3		99.8	99.2	103.7	103.7
Secondary, all programmes	87.4	82.7		85.6	87.8	89.1	90.8
Lower secondary, all programmes	79.5	95.5		97.9	98.8	99.8	99.5
Upper secondary, all programmes	75.3	75.9		79.1	82.1	83.7	86.4
Net enrollment rate[b]							
Primary	89.6						89.7
Secondary, all programmes							
Percentage of repeaters per grade							
Primary, all grades	2.44	2.01		2.26	1.95	2.44	2.22
Primary, grade 4	2.21	2.54		2.63	2.26	2.38	1.68
Secondary, all grades	4.29	2.68		2.42	2.23	2.74	2.76
Secondary, grade 2				1.17	0.99	1.23	1.22

Source: UNESCO, WEI program.

Notes: [a] The gross enrollment ratio is the ratio of all children enrolled in these grades over the total number of children with the right age to be enrolled in these grades. [b] The Net enrollment rate is the ratio of the population in the grades of interest with the adequate age over the population of that age.

Table 4A: The effect of Circumstance Variables on Test Scores, SIMCE 2001 and 2006

	Spanish		Mathematics	
	2001	2006	2001	2006
Female	8.29	7.77	-9.08	-9.65
	[0.21]***	[0.20]***	[0.22]***	[0.25]***
Father with secondary education	3.19	3.18	2.43	3.70
	[0.27]***	[0.27]***	[0.28]***	[0.33]***
Father with college education	14.97	16.42	18.53	21.25
	[0.39]***	[0.39]***	[0.40]***	[0.48]***
Mother with secondary education	7.12	8.79	6.82	11.13
	[0.27]***	[0.27]***	[0.28]***	[0.33]***
Mother with college education	19.26	23.83	22.40	30.29
	[0.39]***	[0.39]***	[0.40]***	[0.48]***
Second grouping of departments for school location	4.59	6.48	5.92	8.85
	[0.26]***	[0.24]***	[0.26]***	[0.30]***
Third grouping of departments for school location	8.67	9.26	10.90	12.27
	[0.26]***	[0.25]***	[0.27]***	[0.31]***
Parental income between $200 and $500	12.10	8.10	11.16	11.15
	[0.25]***	[0.26]***	[0.26]***	[0.32]***
Parental income higher than $500	33.14	20.60	41.64	31.03
	[0.39]***	[0.37]***	[0.40]***	[0.46]***
Constant	223.66	226.81	224.97	225.98
	[0.26]***	[0.24]***	[0.27]***	[0.30]***
Observations	192185	225136	191859	225078
R squared	0.16	0.16	0.22	0.18

Notes: All the regressions used OLS models, and standard errors are in brackets. The department were grouped according to students's scores, so that each group includes about one third of the students in the sample. The second group is composed by Arauco, Cachapoal, Cautín Sur, Chiloé, Choapa, Colchagua, Concepción, Curicó, Elqui, Linares Magallanes, Palena-Chaitén, Talca, Valparaíso and Ñuble. The third group is composed by Coihaique, Cordillera, Llanquihue, Osorno, Santiago Centro, Santiago Oriente, Santiago Poniente and Valdivia. All the other departments were includied in the reference group. * significant at 10%, ** significant at 5%, ***significant at 1%

Table 4B. The effect of Circumstance Variables and School Type on Test Scores, SIMCE 2001 and 2006

	Spanish		Mathematics	
	2001	2006	2001	2006
Female	8.43	7.91	-8.94	-9.45
	[0.21]***	[0.20]***	[0.21]***	[0.24]***
Father with secondary education	3.28	3.39	2.79	4.04
	[0.27]***	[0.27]***	[0.27]***	[0.33]***
Father with college education	12.28	13.76	14.58	17.30
	[0.38]***	[0.39]***	[0.39]***	[0.48]***
Mother with secondary education	6.92	8.74	6.78	11.12
	[0.26]***	[0.27]***	[0.27]***	[0.33]***
Mother with college education	16.36	20.54	18.24	25.42
	[0.39]***	[0.39]***	[0.39]***	[0.48]***
Second group of departments for school location	5.03	6.77	6.19	9.21
	[0.25]***	[0.24]***	[0.26]***	[0.30]***
Third group of departments for school location	6.32	7.42	7.73	9.56
	[0.26]***	[0.25]***	[0.26]***	[0.31]***
Parental income between $200 and $500	11.59	8.01	10.91	11.13
	[0.25]***	[0.26]***	[0.25]***	[0.32]***
Parental income higher than $500	22.32	13.33	25.76	20.15
	[0.41]***	[0.39]***	[0.42]***	[0.47]***
Private subsidized school	10.35	8.49	10.57	11.78
	[0.22]***	[0.21]***	[0.23]***	[0.26]***
Private unsubsidized school	32.28	32.50	46.91	48.63
	[0.46]***	[0.49]***	[0.46]***	[0.60]***
Constant	219.58	223.04	220.68	220.74
	[0.27]***	[0.26]***	[0.27]***	[0.32]***
Observations	192185	225136	191859	225078
R squared	0.19	0.17	0.26	0.21

Notes: All the regressions used OLS models, and standard errors are in brackets. The department were grouped according to students's scores, so that each group includes about one third of the students in the sample. The second group is composed by Arauco, Cachapoal, Cautín Sur, Chiloé, Choapa, Colchagua, Concepción, Curicó, Elqui, Linares Magallanes, Palena-Chaitén, Talca, Valparaíso and Ñuble. The third group is composed by Coihaique, Cordillera, Llanquihue, Osorno, Santiago Centro, Santiago Oriente, Santiago Poniente and Valdivia. All the other departments were includied in the reference group. * significant at 10%, ** significant at 5%, ***significant at 1%

Table 5A. The Effect of Circumstance Variables on Test Scores, PISA 2001 and 2006

	Reading		Mathematics	
	2001	2006	2001	2006
Female	22.68	21.90	-9.11	-23.05
	[2.60]***	[3.01]***	[3.66]**	[2.41]***
Father with secondary education	18.86	16.55	21.88	13.98
	[3.40]***	[3.75]***	[4.68]***	[3.00]***
Father with college education	16.86	22.71	21.95	17.33
	[4.68]***	[5.51]***	[6.31]***	[4.34]***
Mother with secondary education	34.78	26.40	29.23	30.27
	[3.32]***	[3.75]***	[4.43]***	[3.01]***
Mother with college education	55.71	53.16	57.03	48.64
	[4.65]***	[5.07]***	[6.15]***	[4.15]***
Father service worker, craft and related trades worker, or plant/machine operator or assembler.	-38.66	-34.10	-38.32	-38.95
	[3.94]***	[4.50]***	[5.18]***	[3.52]***
Father skilled agricultural or fishery workers, with an elementary or a missing occupation	-47.76	-37.43	-50.32	-45.97
	[4.42]***	[5.34]***	[5.94]***	[4.34]***
Town or city (less than 100,000 inhabitants)	11.33	13.87	2.57	20.11
	[4.31]***	[5.21]***	[6.05]	[4.24]***
City or metropolis (more than 100,000 inhabitants)	20.84	36.22	15.33	37.33
	[4.07]***	[4.66]***	[5.62]***	[3.82]***
Constant	380.69	401.35	377.10	395.80
	[5.69]***	[6.41]***	[7.61]***	[5.06]***
Observations	4633	4732	2578	4732
R squared	0.23	0.17	0.2	0.25

Notes: All the regressions used OLS models, and standard errors are in brackets. The dependent variables are given in plausible values in a five point scale. *significant at 10%, ** significant at 5%, ***significant at 1%

Table 5B. The Effect of Circumstance Variables and School Type on Test Scores, PISA 2001 and 2006

	Reading		Mathematics	
	2001	2006	2001	2006
Female	23.00	20.68	-8.96	-24.21
	[2.55]***	[2.95]***	[3.60]**	[2.35]***
Father with secondary education	18.36	16.60	20.46	14.47
	[3.34]***	[3.72]***	[4.60]***	[2.96]***
Father with college education	12.14	18.89	16.59	13.59
	[4.53]***	[5.39]***	[6.11]***	[4.22]***
Mother with secondary education	30.43	25.25	25.21	29.54
	[3.27]***	[3.72]***	[4.42]***	[2.97]***
Mother with college education	42.67	46.66	44.26	42.64
	[4.66]***	[5.03]***	[6.23]***	[4.08]***
Father service worker, craft and related trades worker, or	-29.75	-26.84	-30.95	-31.97
plant/machine operator or assembler.	[3.90]***	[4.44]***	[5.06]***	[3.46]***
Father skilled agricultural or fishery workers, with an	-37.71	-28.22	-41.52	-37.31
elementary or a missing occupation	[4.36]***	[5.29]***	[5.85]***	[4.29]***
Town or city (less than 100,000 inhabitants)	14.46	18.05	5.85	23.13
	[4.19]***	[5.11]***	[5.94]	[4.18]***
City or metropolis (more than 100,000 inhabitants)	20.25	32.96	14.96	33.93
	[3.90]***	[4.54]***	[5.48]***	[3.75]***
Private subsidized school	15.63	25.63	17.07	19.84
	[2.88]***	[3.20]***	[4.10]***	[2.58]***
Private unsubsidized school	53.68	54.31	52.03	53.11
	[3.91]***	[5.45]***	[5.39]***	[4.37]***
Constant	365.28	383.02	362.64	380.36
	[5.70]***	[6.48]***	[7.59]***	[5.19]***
Observations	4633	4732	2578	4732
R squared	0.26	0.19	0.23	0.27

Notes: All the regressions used OLS models, and standard errors are in brackets. The dependent variables are given in plausible values in a five point scale. *significant at 10%, ** significant at 5%, ***significant at 1%

Table 6. Inequality of Opportunity for Achievements in Mathematics and Spanish for SIMCE surveys

	Mathematics						Spanish					
	2001		2006				2001		2006			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Total inequality	0.023	0.023	0.033	0.033	0.033	0.033	0.020	0.020	0.021	0.021	0.021	0.021
Non parametrically smoothed	**0.225**	**0.279**	**0.184**	**0.221**	**0.191**	**0.225**	**0.169**	**0.203**	**0.159**	**0.187**	**0.165**	**0.190**
Non parametrically standardized	**0.237**	**0.289**	**0.161**	**0.192**	**0.166**	**0.195**	**0.159**	**0.190**	**0.145**	**0.171**	**0.151**	**0.173**
Parametrically standardized	**0.220**	**0.261**	**0.181**	**0.206**	**0.185**	**0.207**	**0.165**	**0.189**	**0.156**	**0.173**	**0.159**	**0.175**
Partial Effects												
Only gender	0.008	0.008	0.006	0.006	0.006	0.006	0.006	0.006	0.005	0.005	0.005	0.005
Only father's education	0.071	0.059	0.071	0.060	0.064	0.055	0.053	0.045	0.063	0.055	0.056	0.050
Only mother's education	0.081	0.069	0.093	0.081	0.087	0.078	0.065	0.058	0.085	0.076	0.080	0.073
Only father's occupation					0.034	0.023					0.034	0.026
Only school location	0.017	0.013	0.013	0.010	0.013	0.010	0.012	0.009	0.012	0.010	0.011	0.009
Only parental income	0.144	0.102	0.093	0.069	0.085	0.063	0.105	0.080	0.072	0.053	0.064	0.047
Only type of school		0.147		0.094		0.092		0.090		0.071		0.069
Only ethnicity					0.003	0.002					0.002	0.001
R2	0.220	0.261	0.181	0.206	0.185	0.207	0.165	0.189	0.156	0.173	0.159	0.175
Observations	192149		225078				192326		225136			

Notes: The generalized entropy index E(2) was used here.

Table 7. Inequality of Opportunity for Achievements in Mathematics and Reading for PISA surveys

	Mathematics				Reading			
	2001		2006		2001		2006	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total inequality	0.030	0.030	0.023	0.023	0.024	0.024	0.027	0.027
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Non parametrically smoothed	**0.248**	**0.332**	**0.291**	**0.358**	**0.272**	**0.343**	**0.221**	**0.291**
	[0.027]	[0.034]	[0.029]	[0.036]	[0.023]	[0.027]	[0.031]	[0.039]
Non parametrically standardized	**0.202**	**0.268**	**0.271**	**0.330**	**0.232**	**0.290**	**0.185**	**0.243**
	[0.023]	[0.03]	[0.027]	[0.033]	[0.022]	[0.025]	[0.028]	[0.035]
Parametrically standardized	**0.200**	**0.233**	**0.264**	**0.287**	**0.237**	**0.272**	**0.187**	**0.209**
	[0.021]	[0.020]	[0.027]	[0.029]	[0.021]	[0.021]	[0.026]	[0.029]
Only gender	0.001	0.001	0.025	0.025	0.021	0.021	0.005	0.006
	[0.002]	[0.002]	[0.007]	[0.007]	[0.007]	[0.007]	[0.004]	[0.004]
Only father's education	0.055	0.045	0.049	0.042	0.052	0.042	0.046	0.041
	[0.015]	[0.015]	[0.013]	[0.012]	[0.013]	[0.013]	[0.013]	[0.012]
Only mother's education	0.109	0.094	0.130	0.122	0.131	0.114	0.091	0.084
	[0.014]	[0.015]	[0.017]	[0.017]	[0.012]	[0.012]	[0.016]	[0.016]
Only father's occupation	0.099	0.087	0.105	0.092	0.102	0.087	0.067	0.057
	[0.015]	[0.015]	[0.017]	[0.015]	[0.011]	[0.012]	[0.016]	[0.015]
Only school location	0.026	0.023	0.072	0.065	0.031	0.028	0.054	0.050
	[0.019]	[0.019]	[0.024]	[0.022]	[0.023]	[0.022]	[0.023]	[0.021]
Only type of school		0.098		0.079		0.108		0.068
		[0.018]		[0.028]		[0.023]		[0.023]
R2	0.197	0.230	0.273	0.300	0.225	0.260	0.186	0.208
Observations	2578		4732		4633		4732	

Notes: The generalized entropy index E(2) was used here, and test scores were measured with plausible values. Bootstrapped standard errors in brackets.