# Mind the Gap.
# Irrevocable Wage Differentials in Chile

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# Abstract

Using a longitudinal database that follows individuals from their last years of schooling to their first years at labor market we apply a decomposition methodology in order to understand the wage differentials among school types in Chile. With micro-simulations exercises we can isolate the impact on wages of changes in the academic achievements of individuals and changes in their associated returns in labor market.

Our results show that even when adding one extra standard deviation to the test score achieved by the most vulnerable individuals at high school, there is a considerable difference in the endowments returns between groups that makes almost impossible to close the existent wage gap between them at labor market.

In this way, as long as the prices of the academic achievement in the labor market remain constant, no public policy or major investment e orts will succeed in eliminating the wage differentials between school types.

## 1. Introduction

As recognition of his great economic performance during the '90s, Chile joined the OECD in 2010, becoming the first nation from South America to sign an accession agreement, and later, in 2013 joined the group of high income countries according to the World Bank classification.

Between 1990 and 2015 the GDP growth of the Chilean economy reached an annual rate of 4.8%, which is considerably high if it is compared with the annual growth rate of 2.85% reached by the world in that period.

This massive economic growth allowed an increase in the GDP per capita (PPP) from US$ 4,407 in 1990 to US$ 22,316 in 2015, and derived in a significant reduction of poverty, such that the proportion of the population considered to be poor fell from 38.6% to 7.8% between 1990 and 2014.

But, despite this rapid economic growth and improvements in the poverty ratios, the wage inequality has remained stable at a high level: at 2014 Chile was the OECD country with the highest level of inequality, with a Gini coefficient of 0.465.

This inequality is reflected in huge wage gaps. According to the OECD Income Distribution Database, by 2014 the richest 20% of the population earned 10.6 times more than the poorest 20%. But this difference turns even more significant when comparing against top incomes: Lopez et al. (2013) conclude that the personal income share of the richest 1% of the population accounted for 30% of total incomes, and the richest 0.1% earned a 17% of total incomes.

The high and persistent income distribution in Chile has led several authors to study its causes, and many of them found an important role for education in explaining these problems. It has been widely documented that one of the main problems in the Chilean education is the quality differences between school types, which redounds in differential access to tertiary education and later, in wage inequality.

Since 1980s, the Chilean educational system has undergone several reforms. One of this was the implementation of a co-payment regime, which added the possibility of selecting students and that has resulted in a highly segregated education: most vulnerable students mainly attend to public establishments, while students from the highest socioeconomic level, in a large percentage, attend to private schools that represent only 7% of schools in Chile.

The possibility of selection and the high costs of the private education has resulted in a grouping of students according to their socioeconomic status and academic records, which has consequences on the academic performance, negatively affecting the most vulnerable students: there is evidence that in Chile the socioeconomic status of the students is positively correlated with their academic achievements and that teaching quality worsens among bad academic performance students, so in classes with low-ability students time is used in a less efficient way.

All these factors that characterize the Chilean educational system have resulted in highly segregated education. According PISA 2012, Chilean results are far below the OECD average: Chile ranked in the 51th place among 65 countries in the test scores and 52% of their students don't have a minimum base to face math challenges. Nonetheless, this average hides important information: while the average test score achieved by the private-fee-paying schools is higher than the OECD average, public funded schools scores are far below it, such that the knowledge gap among public and private schools is equivalent to three years of schooling.

Trying to understand these huge differences between school types, several authors has studied the segregation of the Chilean educational system and explored different reasons to explain these problems. Mizala and Romaguera (2000) show that the differences in the test score achieved by the different school types can be explained by the amount of resources available for the private-fee-paying schools, which have much more resources since they are funded by parents. In the same line of research, Mizala, Romaguera & Farren (2002) studied the technical efficiency of schools in Chile, which is defined as the capacity of schools to generate the maximum academic achievement given the quantity of inputs they use, concluding that the private-fee-paying were the most efficient: a 90% of this schools were classified in the most efficient quadrant, while only a 59% and a 39% of the private-voucher and public school reached that classification.

In brief, private schools have greater resources available, but also, use them in a more efficient way. Given this, we can understand the differences in the performance in standardized test and the later wage gaps between school types.

Given this background and by using longitudinal data, Urzúa et al. (2016) show the mechanisms that link the education and adult wage heterogeneity, providing evidence of how important is the type of education received to explain differences in the performance at labor market: even after controlling for individual academic achievement at high schools, they found that there is a huge inequality among school types and that human capital investments returns are higher for individuals educated in private-fee-paying schools.

The problem seems to arise from the fact that public schools have poorer resources than private schools and that they receive more vulnerable individuals. Therefore, individuals who attended public schools do worst on cognitive test and are less prepared for tertiary education and for the labor market, which is a direct consequence of “skills begetting skills". The evidence points that Chilean education, besides not helping to reduce the initial gaps, is increasing them and perpetuating the existent inequality. Thus, the question we will try to answer in this article is whether it is possible or not for an individual coming from a public funded school (both public and private-voucher schools) to close the wage gap maintained with their peers of private schools.

To answer this question, we will first document the existent wage gap among school type and then simulate changes in the academic achievements of the individuals educated in public funded schools in order to evaluate the impact on their future wages. The model that we will use to do so follows Bourguignon, Fournier and Gurgand (2001) and applies a decomposition method in order to decompose wages in its determinants for the three types of schools. This decomposition allows us to carry out simulations of changes in those parameters and evaluate the wage convergence between groups.

This methodology has already been applied for the Chilean case by Bravo, Contreras & Urzua (2002) who analyzed inequality and poverty on cross sectional data from 1990 and 1998. They found that while poverty responded strongly to the simulation exercises, inequality was less sensitive and remained stable in time. Also, Larrañaga & Valenzuela (2011) measured the impact on inequality of changes in income determinants between the years 1990 and 2003 and documented that there were certain factors that could have diminish poverty between those years at the cost of a worst income distribution, such as the increases in education returns. Both of these articles use cross sectional data.

Our investigation contributes to what has already been done because of the unique database to which we have access and the better estimations it allows us to develop. This data is constructed from administrative records and follow the trajectory of 103,424 individuals from 2003 -when they were 15-16 years old and took a standardized test in high school- until their first years in the labor market- when these individuals where 25 years old and earned monthly wages-. This data allow us to evaluate the impact on wages earned by the individuals at 2012, if in 2003, when they were still in high school, they would have achieved better scores in the standardized test.

Also, this longitudinal database provides us with rich information about their family and educational characteristics, their academic achievements and some labor market characteristics. Thus, our investigation differs from what has already been done for two main reasons.

Firstly, instead of analyzing data at household's level, we can look at wage differentials at the individual level, so we can capture individual level heterogeneity which is very important when analyzing wage differentials. Secondly, as we use longitudinal data, we estimate the wages of the individuals, but controlling for pre-labor market variables such as their school attendance and academic achievements when they where 15-16 years old and some familiar characteristics reported by parents at their last years in high school. Therefore, we can reduce the effect of the non-observables that would bias our estimates if we have used cross sectional data.

In this way, our estimates are more accurate, resulting in a better wage decomposition and thus, in better simulation exercises and more reliable conclusions from what has already been done.

Our main findings show us that even when adding one standard deviation in the test score achieved by the most vulnerable individuals, there is a considerable difference in the endowments returns between groups that makes the existent wage gap between school type irrevocable.

After this introduction, the article will be structured as follows. Section 2 describes the Chilean educational system and the types of secondary education establishments. Section 3 details the preparation process of our final data and presents some descriptive statistics. Section 4 presents our empirical strategy. Sections 5 and 6 document the results of our simulations and develop some robustness checks. And finally, section 7 concludes.

## 2. The Chilean Educational System

During the 1980s the Chilean educational system underwent some reforms that included the decentralization of the public schools by transferring the administration from the Ministry of Education to Municipal Authorities and also included a voucher system for both publicly and privately administrated schools.

From then on, the primary and secondary establishments can be distinguished in three types of schools according to their administration and financing, as seen in Table 1.

Public schools are those whose administration and funding depends on the public sector. Private-vouchers schools are also financed by the State but managed by the private sector. Finally, private-fee-paying schools are both managed and funded by the private sector.

The main difference between public and private-vouchers establishments is that private-voucher can charge tuition and can select their students based on their own criteria, as well as private-fee-paying establishments.

Table 1: Types of schools by administration and financing

| | | **Administration** | |
|---|---|---|---|
| | | Public | Private |
| **Financing** | Public | Public | Private-voucher |
| | Private | - | Private-fee-paying |

Both, primary and secondary education are compulsory for all Chileans. Primary education is composed of eight years of schooling, generally taught between the ages of seven and fourteen. Then, secondary education, which has a duration of four or five years and can be separated into humanistic or technical. Technical secondary education is mainly designed for students who after obtaining a technical diploma want to enter the labor market at an early age.

In order to measure the quality of teaching of the establishments, during primary and secondary education, the Ministry of Education applies the SIMCE test (System of Measurement of Quality of Education, for its acronym in Spanish), a standardized test that must be taken by every student nationwide in the levels evaluated.

Once approved the secondary education, the students can choose to enter the tertiary education. This step in the Chilean educational trajectory is very important due to the high returns that this level education still has. According to Ruiz-Tagle (2007), despite the increase of the share of tertiary educated workers, there has been no evidence showing a decline in returns to tertiary education since the 90s in

Chile. This implies that the differences in returns for the different levels of education are key to determine the wage inequality.

The higher returns within tertiary education are obtained in universities. These entities are divided between CRUCh and private universities. Then, with lower returns on wages there are the professional institutes and technical training centers.

Those students who want to study in universities must take the University Selection Test (PSU). The score of this test is weighted with academic performance in secondary education, which provides a measure that allows schools to select the students they will receive each year. Tertiary education in Chile is paid for and has a high cost.

This is why primary and secondary education are so important. A student who received a good primary and secondary education will be more likely to enter higher education due to the probability of obtaining a higher score in the PSU, with which he will be more likely to obtain funding and hence, in the future he will have higher returns on wages.

## 3. The Data

We use a longitudinal database that follows individuals through almost nine years of their lives, from 2003, when they were at their second year in high school at age 15-16 and took a standardized test (SIMCE), until 2012 when they were 24-25 years old and declare to be working. This database allows us to relate school achievements with labor market performance by looking the average monthly wages they were earning by 2012.

Our database collects information from different administrative sources that contain different data for the same individuals: it merges SIMCE 2003 with RECH-SIGE and SIES data (Chilean Students Register and Tertiary Education Information Service) observations from 2003 to 2010, and with the unemployment insurance database.

From the SIMCE database we obtain the standardized test results, together with some family background information that is available from the parents' questionnaire. RECH-SIGE and SIES allows us to distinguish the gender, the school type, and plenty of information about tertiary education of each registered student. Finally, from the Unemployment Insurance database we can obtain information about the economic activity, the type of contract and the average monthly wages. This is a very unique database for Chile and it allows us to link important information about family background, educational characteristics in secondary and tertiary education, and school attainment with the labor market performance.

Table 2 presents the average of the key variables as we clean and merge the SIMCE and Unemployment Insurance databases. Our sample allows us to make our analyses for 103,424 individuals.

Table 2: Descriptive Statistics by Data Set

| | SIMCE | Valid Observations | Earnings 2012 |
|---|---|---|---|
| Men | 0.50 | 0.50 | 0.56 |
| Age | 24.90 | 24.88 | 24.91 |
| Math SIMCE | 247.83 | 247.39 | 239.86 |
| Language SIMCE | 254.26 | 253.39 | 247.22 |
| Public | 0.48 | 0.47 | 0.49 |
| Private-voucher | 0.40 | 0.40 | 0.40 |
| Private-fee-paying | 0.12 | 0.13 | 0.11 |
| Family Income | 1.23 | 1.51 | 1.33 |
| 2012 wages | $756.16 | $775.58 | $775.58 |
| Observations | 237,306 | 173,671 | 103,424 |

Notes: This table presents different data sets and averages of key variables as we "clean" and merge the SIMCE and Unemployment Insurance databases. The first column (SIMCE data) corresponds to the original SIMCE 2003 data. The second column (Valid obs.) drops observations with missing or incoherent values in the SIMCE database, by looking especially at the values of wage variables, SIMCE scores and the age of individuals. The third column (Earnings 2012) shows the statistics of the students that took the SIMCE test in 2003 and who were affiliated to the unemployment insurance system by 2012. In that way we only considered the individuals who reported monthly earnings in 2012.

As expected, when merging the educational and labor trajectories we loss about 130.000 individuals mainly because problems with the test score and because we leave out the individuals who weren't earning wages at 2012. This can cause bias in our estimations because of data selection: our final database has higher men participation and higher average incomes. This problem arises because workers who report their wages in the Unemployment Insurance database are formal workers, and only 72.8% of workers are formal according to CASEN 2011. This would bias our results upward because informal workers earn about 48.2% of what formal workers earn. Another bias source is the fact that by 2012 there could be many individuals who were still studying instead of working in the formal labor market. The direction of this bias isn't obvious. The reason we are not observing those individuals might differ: it could be because of failing or because they are studying longer careers or specializing.

Tables 14 and 15 in Appendix show descriptive statistics for all the variables of our final sample. It can be seen that in 2012 the individuals where 25 years old on average, 55.6% were men and 83% lived in urban zones. 49.2%, 39.8% and 11% attended public, private-voucher and private-fee-paying schools respectively. The average schooling years after 2003 are 4.74, 88% finished their secondary education and 11% of the sample got a tertiary studies diploma. By 2012, the average effective experience was of 40 months.

Given that this paper analyzed differences among school types, it is important to describe them. In Table 3 it can be seen that those educated in private-fee-paying schools overcome those educated in public funded schools in academic achievements and wages. Also, it shows that while there are no differences in individual characteristics, there are significant differences in family background characteristics. Those who attended private-fee-paying schools have more educated parents and come from richer families than those who attended private-voucher and public schools. Also, a higher proportion of students from private schools finished their secondary and tertiary studies.

Likewise, Table 3 shows the endowment differences among school types. It is interesting to note that although the average school attendance and the average school grades are similar among the three groups, there are significant differences in SIMCE test scores and in schooling years after SIMCE. These differences favor those who studied in private-fee-paying schools and are amplified with the years. While, in 2003 public school students score on average 84.1% of the score achieved by the private-fee-paying students in the math test score, this percentage falls to 73.8% when we compare their average wages earned in 2012. The same happens between private-voucher schools and private-fee-paying schools.

Table 3: Individual, Family and endowment characterization by school type

| Variable | Public | Private Voucher | Private |
|---|---|---|---|

| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
|---|---|---|---|---|---|---|
| **Family and Individual Characteristics** | | | | | | |
| Men | 0.56 | 0.50 | 0.55 | 0.50 | 0.57 | 0.50 |
| Age | 24.97 | 0.85 | 24.87 | 0.78 | 24.81 | 0.66 |
| Family Income | 1.13 | 0.43 | 1.35 | 0.72 | 2.19 | 1.74 |
| Urban Zone | 0.81 | 0.39 | 0.84 | 0.36 | 0.84 | 0.37 |
| Father education | 1.92 | 1.18 | 2.38 | 1.46 | 3.13 | 2.06 |
| Mother education | 1.80 | 1.09 | 2.25 | 1.38 | 2.90 | 1.89 |
| Finish Secondary Education | 0.85 | 0.35 | 0.90 | 0.31 | 0.97 | 0.18 |
| Finish Tertiary Education | 0.08 | 0.26 | 0.13 | 0.33 | 0.17 | 0.38 |
| **Endowments Levels** | | | | | | |
| School Attendance | 92.60 | 8.00 | 93.80 | 7.80 | 92.30 | 13.10 |
| School Grades | 5.30 | 0.60 | 5.40 | 0.60 | 5.60 | 0.59 |
| Math SIMCE | 228.30 | 52.20 | 245.40 | 55.00 | 271.40 | 60.20 |
| Language SIMCE | 238.50 | 46.20 | 252.50 | 47.10 | 267.30 | 47.60 |
| Scholarship | 4.30 | 1.90 | 5.00 | 2.00 | 5.40 | 2.10 |
| 2012 wages | 727.60 | 483.80 | 776.50 | 510.50 | 986.50 | 694.90 |
| Observations | 50,845 | | 41,178 | | 11,401 | |

Notes: Family income and parent education are obtained from SIMCE 2003 parent's questionnaire and are reported on tranches, which can be seen in Table 14 in Appendix. School attendance represents the average attendance during the last three years of secondary education. School grades represent average grades from the student in 2003. Finally, years of schooling represents additional years of study after SIMCE 2003, when they already had 10 years of schooling.

## 4. Methodology

It has been widely documented that there are wage inequalities between school types in Chile and that this differences started at school because of the quality differences between school types and in consequence because of the great gaps in academic achievements.

With this investigation we want to simulate what would have happened with the wages of the individuals educated in public and private-voucher schools in their first years at labor market if they have had higher academic achievements at high school. Also, in a second simulation we want to evaluate the impact on wages after changing the returns on wages of the academic achievements of the individuals educated in public funded schools.

Taking advantage of our longitudinal data, we simulate the effect of these changes in order to understand how the wage gap among school types could be closed.

We follow a model developed by Bourguignon, Fournier & Gurgand (2001), who analyzed the Taiwanese case for the period 1979-1994, when the country reduced poverty significantly, but did not alter its income distribution. These authors applied a decomposition methodology based on micro-simulation techniques that allowed them to show which factors where determinant of that phenomenon.

The same methodology was applied to the Chilean case by Bravo, Contreras & Urzúa (2002) and Larrañaga & Valenzuela (2011), who simulated inter-temporal changes in the determinants of the households' income in Chile. These authors, by imposing the distributional structure of one year into another year, could understand which factors determined a reduction in poverty and which factors allowed that the income distribution remains stable over years.

Larrañaga & Duryea (2011) contributed to the literature when doing the first comparisons between countries to examine the income inequality of Chile. In particular, they examine the case of Uruguay, a country with much lower levels of inequality than Chile, in order to use their parameters to simulate changes in the Chilean income distribution.

Also, Ruiz-Tagle (2007) developed simulations in order to forecast the wage inequality in Chile for ten years by looking the hourly wages of Chilean men. He studied the phenomenon of the ageing of the Chilean population and the higher levels of education of the younger cohorts of workers and found two main results. Firstly, by decomposing the inequality by groups of education and groups of age he found that most of the inequality comes from within the groups. And secondly, his forecast proposed that there was not expected that the wage inequality would be reduced significantly between 2007 and 2017.

Our investigation contributes to what has already been done because of the unique database to which we have access and the better estimations it allows us to develop. This data is constructed from administrative records and follows the trajectory of 103,424 individuals from their last years in school until their first years in the labor market. This database provides us with rich information about their family and educational characteristics, their academic achievements and some labor market characteristics. So, our investigation differs from what has already been done for two main reasons. Firstly, instead of analyzing data at household levels, we can look differences at the individual level, so we can capture individual level heterogeneity which is very important when analyzing wage differentials. Secondly, as we use longitudinal data, we estimate wages controlling for previous variables such as the academic achievements, the school attendance and some familiar characteristics reported by parents at the last years in school. Therefore, we can eliminate the effect of the unobservable that would affect our estimates if we would have used cross sectional data.

In particular, we will evaluate the impact on wages of changes in parameters associated to academic achievements of the individuals educated in public funded schools. In order to do so we developed two types of simulations. In the first one we changed the SIMCE test score they achieved at 2003 and in a second simulation we changed the prices associated to this test score in the labor market. We call the impact on wages of these two types of simulations as the Endowment Effect and the Price Effect respectively.

There are many reasons why we focus our simulations on the SIMCE test score. Firstly, this is an standardized test that measures the knowledge and math capabilities of the students, so the score reflects their skills, specially their cognitive skills, which have a considerable impact on wages.14 Secondly, it has been widely documented that in Chile the academic achievements reflects the family background of the students such as the socioeconomic level, the parents education, and the importance that the family gives to the education. A third reason is that the score obtained by a student reflects the quality of education provided by the educational establishments and the level of resources they have. Finally, it is interesting to use this test score because, given that this is a variable that public policies can improve, it is usually used as an instrument to evaluate educational programs in Chile. In this way, our result would be more interpretable, and could be a contribution for understanding the problems behind the differences in outcomes between school types and for a better management of public policies that seek to eliminate these problems.

This test score involves important information of the students, so it is the most appropriate variable to evaluate with our simulations.

## 4.1 Micro-simulations

We will assume that the labor incomes of an individual “i" at 2012 depends on the following arguments: (1) their individual skills, $S_{it}$; (2) other factors, $Z_{it}$, such as their individual characteristics, the educational characteristics and labor conditions; and (3) the prices of the labor market $\theta_{it}$. Thus, the income function can be represented as:

$$W_{it} = W(S_{it}; Z_{it}; \theta_{it})$$

Due to the lack of data on skills, we will represent the individual skills with a standardized test score $T_{i\bar{t}}$, taken by the individuals at 2003. As we want to evaluate the impact of changes in the test score and in its returns on wages, we will decompose the price vector $\theta_{it}$ in the prices for the test score, $\beta_{it}$, and in a vector $\gamma_{it}$ for the coefficients associated to the other wage determinants $Z_{it}$. Thus, we will represent the incomes function as:

$$W_{it} = W(\beta_{it} \cdot T_{i\bar{t}}\,;\, \gamma_{it} \cdot Z_{it})$$

From this function, using an OLS model with the standard errors of Eicker-White, we will estimate the following equation for each group of individuals with the objective of decomposing the wages into the various factors that determine their magnitude:

$$logY_i^j = \alpha_i^j + \beta_i^j \cdot T_i^j + \gamma_i^j \cdot Z_i^j + \varepsilon_i^j$$

Our parameters of interest are $\beta_i^j$ and $T_i^j$, while $Z_i^j$ and $\gamma_i^j$ are vectors of the other explanatory variables and their associated returns respectively.

Using the information related to the parameters estimated from the equation (3) we can run our simulations. For the Endowment Effect we will keep constant the price vector and we will change the level in the math test score obtained by the individuals in 2003, while for the Price Effect we will change the returns associated to the math test score but we will keep constant the level of the test score.

The evidence has shown as that the establishment “j” in which an individual was educated determines to a large extent the level of endowments with which he enters to the labor market. In addition, we know that the high school establishments are associated with different prices in the labor market such that some groups will be more or less rewarded for their levels of endowments and in particular for their academic achievements.

This methodology will allow us to analyze the levels of convergence in wages between the individuals educated in public funded schools and individuals educated in private schools after changing the parameters associated with their academic achievements.

### 4.1.1. Endowment Effect

The Endowment Effect (E.E.) quantifies the impact on wages that would have had a change in the score of the SIMCE obtained by the individuals educated in public funded schools. So, given the prices of the labor market for each group of individuals, we will evaluate how does the wages of the individuals educated in public funded schools moves when changing this pre-labor market characteristic. For simplicity, we will simulate these changes on the test scores in terms of one standard deviation.

Thus, the Endowment Effect will be the difference between the new simulated wages and the original wages.

$$E.E. = W'\left(\beta_i^j \cdot T_i^{j\prime}, \gamma_i^j \cdot Z_i^j\right) - W\left(\beta_i^j \cdot T_i^j, \gamma_i^j \cdot Z_i^j\right)$$

Where $T_i^{j\prime}$ represents the new simulated test score:

$$T_i^{j\prime} = T_i^j + SD_{SIMCE}$$

The objective is to evaluate if there is a convergence in wages between individuals educated in public funded schools and those educated in private schools. From Table 3, we know that there is a gap in the math test scores between these groups: while the individuals educated in public and private-voucher schools achieved an average score of 228 and 245 respectively, the individuals from private-fee-paying schools achieved in average a score of 271.

So, when adding one extra standard deviation to the test score achieved by the individuals educated in public-funded establishments, we are closing that gap in their academic achievements, so that we could evaluate the impact on their future wages and how this simulation closes the wage differences between school types.

### 4.1.2. Price Effect

The Price Effect (P.E.) quantifies the impact on 2012 wages that would have had a change in the prices associated to the SIMCE test score achieved by the individuals at 2003, when they where 15-16 years old.

As it is documented in our results, the labor market premium for academic achievements is substantially greater for the individuals that studied in private-fee-paying schools than for those who did it in private-vouchers and public schools.

So, keeping constant the level of the math SIMCE achieved by each individual, we will simulate changes in the labor market prices for the math test score. In particular, we will replace the associated return of the individuals educated in public funded schools with the average return associated to the individuals educated in private-fee-paying schools.

In this way, we will see how future wages would have behaved if academic performance had been equally valued for all individuals regardless of the type of establishment where they received their secondary education. The differentials in wages due to these simulations represent the Price Effect.

$$P.E. = W'\left(\beta_i^{j\prime} \cdot T_i^j, \gamma_i^j \cdot Z_i^j\right) - W\left(\beta_i^j \cdot T_i^j, \gamma_i^j \cdot Z_i^j\right)$$

Where $\beta_i^{j\prime}$ is the labor market return of the SIMCE test score for individuals educated in private-fee-paying schools.

Thus, in spite of maintaining the academic achievement gap between the different school types, we will be able to evaluate the convergence in wages produced by the change in the returns on wages of the test score achieved by each group of individuals.

## 5. Results

In this section we present the results of the different simulations that were explained from a theoretical perspective in Section 4.

Both, the Endowment Effect and the Price Effect were applied on individuals who studied in public funded schools in order to evaluate how it would be possible to close the wage gap maintained with the individuals who studied in private-fee-paying schools.

Table 4 show the results of the regressions corresponding to equation (3) from which we obtained the parameters to perform our simulations. It can be seen that the returns to math test score are considerably higher for the individuals educated in private-fee-paying schools, as well as the returns to the school grades and the level of the family incomes.

Table 4: Results for the regression by school type

| VARIABLES | Public<br>lnW | Private-voucher<br>lnW | Private-fee-paying<br>lnW |
|---|---|---|---|
| Math Simce | 0.000479*** | 0.000506*** | 0.000989*** |
| | -0.0000692 | -0.0000786 | -0.000162 |
| Language Simce | -0.0000384 | -0.00013 | -0.000470*** |
| | -0.0000702 | -0.0000829 | -0.000171 |
| School grades | 0.0608*** | 0.0844*** | 0.129*** |
| | -0.00523 | -0.00605 | -0.0131 |
| Secondary education | 0.0375*** | 0.0189** | 0.0437 |
| | -0.00733 | -0.00929 | -0.0301 |
| Tertiary education | 0.435*** | 0.434*** | 0.394*** |
| | -0.0114 | -0.00991 | -0.0175 |
| Family income | 0.0589*** | 0.0503*** | 0.0791*** |
| | -0.00725 | -0.00525 | -0.00671 |
| Scholarship | 0.0237*** | 0.0218*** | 0.0225*** |
| | -0.00227 | -0.00245 | -0.00506 |
| Constant | 4.841*** | 9.075*** | -1.445 |
| | -1.252 | -1.519 | -5.07 |
| Observations | 50,845 | 41,178 | 11,401 |
| R-squared | 0.296 | 0.264 | 0.335 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Robust standard errors in parentheses

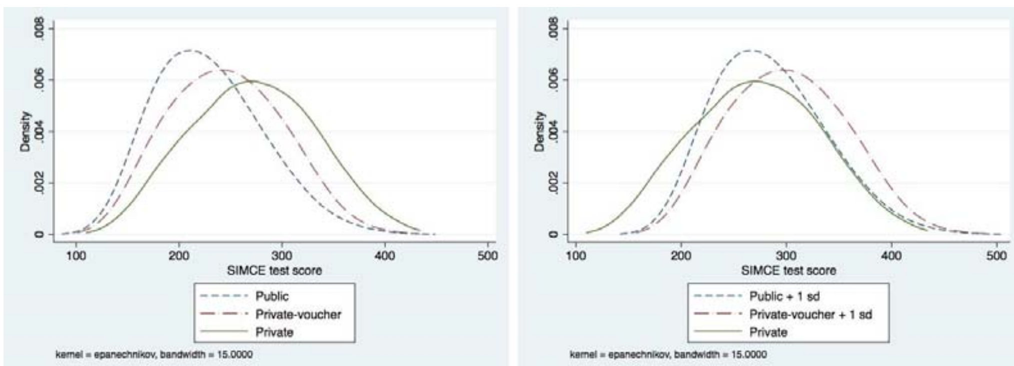
*** p<0.01, ** p<0.05, * p<0.1

## 5.1. Endowment Effect

The Endowment Effect consist in evaluating the impact on wages of the simulation of an increase in the math test score obtained in the year 2003 by those individuals who studied in private funded schools.

Just for simplicity, and for a better interpretation, we will simulate an increase of one standard deviation in the test scores, which is equivalent to 56 extra points in the score obtained. Thus, after applying the Endowment Effect, the SIMCE score distribution of the three groups of individuals tend to look more alike, eliminating the differences observed in this endowment by type of school.

Figure 1: Changes in the SIMCE test score distribution after adding one extra standard deviation.




(a) Original Distribution (b) Simulated Distribution

The results of this first simulations show that after improving the academic achievement of this individuals, their wages, nine years later, remain almost constant. As seen in Table 5, in the year 2012 the individuals who studied in public schools and in private-voucher schools earned an 75,2% and 79,4% of the wages of the individuals educated in private-fee-paying schools, and after this simulation, those percentages moves to 77,2% and 81,7% respectively. That is, the wage gaps were reduced only by a 2% approximately.

Table 5: Summary of the Endowment Effect on 2012 wages

| | Original wage | | Simulated wage | |
|---|---|---|---|---|
| | US$ | % | US$ | % |
| Private-fee-paying | 850.38 | 100 | - | - |
| Private-voucher | 675.09 | 79.4 | 694.49 | 81.7 |
| Public | 639.14 | 75.2 | 656.5 | 77.2 |

Notes: this table summarizes the Endowment Effect for the individuals educated in public funded schools. The results are expressed in US dollars and as a percentage of the wages earned by the individuals educated in private-fee-paying schools.

These results are very unpromising. Increasing the level of this important variable and into that magnitude doesn't have a considerable impact on wages, so the wage differentials remain stable. In order to close the existing gap, keeping the prices constant, we would have to simulate an increase of 6.99 standard deviations in the test scores achieved by individuals educated in private-voucher establishments and an increase of 9.57 standard deviations for the individuals educated in public establishments; changes impossible to achieve.

By looking the impact of different educational programs, we can understand how poor these results are: a program applied in USA (STAR) was very successful, but it increased by between 0.2 and 0.28 standard deviations the test score measured, only a 10% of the increases we just simulated with the Endowment Effect.

The evidence show us that until now, there is no program that could increase in one standard deviation the test scores achieved by students, but even worst, if such a program came to exist, it would not have a considerable effect on reducing the wage differentials by school types in Chile.

With these results, we can conclude that the wage differentials between school types are not determined by the abilities of the individuals. Probably, there are other factors that would explain better this wage gap such as the family income, the network of contact to which each group accesses or differences in the returns to the endowments.

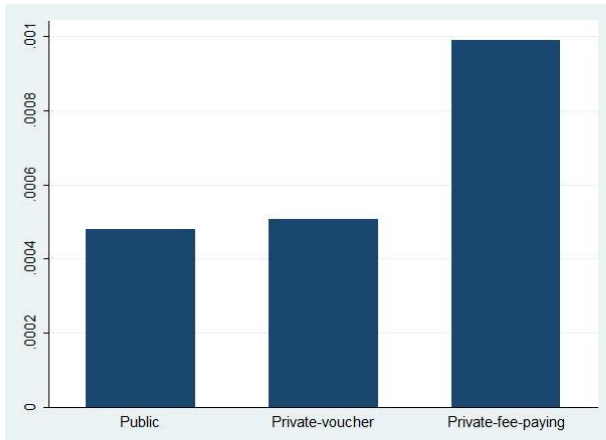
To test this latter hypothesis we will simulate the Price Effect.

## 5.2 Price Effect

From Table 4 we can see that the returns on 2012 wages of the math test score are much greater for the individuals who studied in private-fee-paying schools. This difference is considerable, since their returns correspond to twice the returns of the individuals educated in public funded schools.

There could be many reasons why private-fee-paying schools have a greater return on earnings than voucher and public schools, but we will not refer to those issues in this article.

Figure 2: Return on wages of SIMCE test score by school types




The Price Effect analyses the impact on wages after increasing the returns on wages of the math SIMCE test score obtained by the individuals educated in public funded schools. We replaced the returns of these individuals with the average returns of the individuals who studied in private-fee-paying schools.

Thus, after increasing those coefficients we observe higher wages for them, such that there is a convergence level that is much greater than that achieved in the previous simulations when we increased in one standard deviation their test scores: the Price Effect reduces the wage gap from a 24.84% to 15.34% for the students of public schools, and from a 20.61% to 10.37% for the students of private-voucher schools. That is, the wage gap was reduced approximately in a 10%.

Table 6: Summary of the Price Effect on 2012 wages

| | Original wage | | Simulated wage | |
|---|---|---|---|---|
| | US$ | % | US$ | % |
| Private-fee-paying | 850.38 | 100 | - | - |
| Private-voucher | 675.09 | 79.4 | 762 | 89.6 |
| Public | 639.14 | 75.2 | 719.94 | 84.7 |

Notes: this table summarizes the Price Effect for the individuals educated in public funded schools. The results are expressed in US dollars and as a percentage of the wages earned by the individuals educated in private-fee-paying schools.

Notes: this table summarizes the Price Effect for the individuals educated in public funded schools. The results are expressed in US dollars and as a percentage of the wages earned by the individuals educated in private-fee-paying schools.

## 6. Robustness Check

Our results are alarming as they show us that the wage gap between school types is practically impossible to be closed. Good students, with great academic performances, that come from public funded schools have lower opportunities than their peers who studied in private-fee-paying schools. Nevertheless, we recognize that our methodology has some limitations that could be affecting our results, so we develop a robustness check to reinforce them.

In first place, we will estimate new simulations by changing interest variables others than the math test score in order to evaluate how the wage gap between school types can be closed. Secondly, we will face the selection bias that is implicit in our sample of individuals. And finally, we will evaluate the results of the Endowment Effect by estimating equation (3) with different specifications and methodologies.

### 6.1 Alternative simulations

In order to reinforce the conclusions derived from the simulations of the Endowment Effect estimated in the previous section, we run two alternative simulations: an increase, in one standard deviation, of the educational level of their parents and an increase, in one standard deviation, of the family income reported at 2003 by their parents.

The results of these alternative simulations show us that just as by simulating increases in the SIMCE test score when simulating increases in these two family variables the impact on wages is minimal.

Table 7: Summary of the Endowment Effect and alternative simulations on wages

| | 2012 | % |
|---|---|---|
| Private | 850.38 | 100 |
| Voucher | 675.09 | 79.4 |
| Public | 639.14 | 75.2 |
| Voucher + sd math SIMCE | 694.51 | 81.7 |
| Public + sd math SIMCE | 656.52 | 77.2 |
| Voucher + sd parents ed. | 676.86 | 79.6 |
| Public + sd parents ed. | 643.11 | 75.6 |
| Voucher + sd family income. | 704.74 | 82.9 |
| Public + sd family income | 672.16 | 79 |

Notes: the table summarizes the Endowment Effect when increasing in one standard deviation the math SIMCE score, the parents' education and the family income of the individuals educated in private funded schools. The wages are expressed in US dollars and as a percentage of the wages earned by the individuals educated in private-fee-paying schools.

## 6.2 Sample Selection

The sample we've been working with might present problems associated to a sample bias. The individuals, who compose our sample, by the year 2012, were at different conditions or stages of their lives. While a proportion of them decided to enter tertiary education, another proportion entered directly into the labor market. But also, to that date, there was a fraction of the individuals who entered to the tertiary education who had already completed it, while others were still studying.

Despite we only considered the individuals who were working by 2012 in our final sample, this situation affects our results because we could be overestimating or underestimating the wage gaps between school types.

For example, we can think that the individuals who were still studying were those with better abilities and therefore represented those who would have greater human capital and higher wages. In that scenario, the wage gaps we reported in this study would be underestimated.

But, another possible reason why a proportion of the individuals were still studying by 2012 might be that such individuals have lower skills and found more difficulties to complete their studies. In that case, the observed wage gaps would be overestimated.

In order to face this possible sample bias, in this section we will only consider those individuals who completed tertiary education by 2012. By using this subsample we will be comparing individuals that were at the same situation: with full tertiary education and working. In this way, this group of individuals would not contain the problems explained above.

In Table 8 it can be seen a characterization of this subsample.

Table 8: Summary statistics by sample

| | Full Sample | Subsample |
|---|---|---|
| Public | 0.49 | 0.35 |
| Private-voucher | 0.4 | 0.47 |
| Private-fee-paying | 0.11 | 0.18 |
| Math Simce | 239.9 | 277.1 |
| Language Simce | 247.2 | 278.1 |
| Wages (2012) | 775 | 1160 |
| Observations | 103,424 | 10,984 |

We can realize that, compared with the individuals of the full sample, the individuals who compose this subsample comes in a greater proportion from private-fee-paying schools and private-voucher schools, obtained higher scores in SIMCE and earns higher wages at labor market.

In addition, when comparing the individuals of this subsample by school types, it can be seen a convergence in their scholarship, but they still maintain considerable gaps in their test scores and in their wages.

The data show us that the wage gap by school types are even greater in this subsample, and the results show that after simulating an increase of one standard deviation in the test score, the wage differences were reduced by only a 4% approximately.

The Endowment Effect is greater in this case because the graduates of tertiary education has greater returns on wages to their academic achievements, but it is still a poor result given the huge wage differentials between these groups of individuals.

Table 9: Summary of the Endowment Effect on 2012 wages for graduates

| | Original wage | | Simulated wage | |
|---|---|---|---|---|
| | US$ | % | US$ | % |
| Private-fee-paying | 1,463 | 100 | - | - |
| Private-voucher | 1,111 | 75.9 | 1,162 | 79.4 |
| Public | 1,071 | 73.2 | 1,139 | 77.9 |

Notes: This table summarizes the results of the Endowment Effect for the subsample of the tertiary education graduates.

## 6.3 Alternative Specifications

Another aspect we can review is our specification. As we use many control variables related to the academic achievement our interest variable could be affected and the return observed would not represent his real value. In this way, the return on wages for the test could be lower than expected and therefore the Endowment Effect would be underestimated.

In order to face this potential problem we will run two alternative specifications with the aim of estimating a purest return of the math test score. In a second specification we will not control for the score on the language test and the school grades, and in a third specification, in addition to leaving out the previous variables, we won`t use as independent variables the dummies that indicate if the individuals were graduated from secondary and tertiary education.

As expected, when estimating these new specifications the returns of the math test score increased.

Table 10: Returns of the math Simce by specification and school type

| | Specification 1 | Specification 2 | Specification 3 |
|---|---|---|---|
| Public | 0.000479*** | 0.000695*** | 0.000815*** |
| Private-voucher | 0.000506*** | 0.000797*** | 0.000890*** |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Despite the increases in the returns for the test score, the simulations still throw results that don't change considerably the wage gaps between school types so that the Endowment Effect of one standard deviation on the Simce test score is still insufficient. In the best case, with the third specification, the simulation reduces by 4% the wage gap maintained between individuals from private-voucher schools and those from private-fee-paying schools.

Table 11: Endowment Effect for the different specifications

| | Original wages | | Specification 1 | | Specification 2 | | Specification 3 | |
|---|---|---|---|---|---|---|---|---|
| | **US$** | **%** | **US$** | **%** | **US$** | **%** | **US$** | **%** |
| Private | 850.38 | 100 | - | - | - | - | - | - |
| Private-voucher | 675.09 | 79.4 | 694.49 | 81.7 | 705.88 | 83.0 | 709.56 | 83.4 |
| Public | 639.14 | 75.2 | 656.50 | 77.2 | 664.49 | 78.1 | 668.94 | 78.7 |

Thus, in spite of evaluating the Endowment Effect with higher returns on wages for the test scores, the story that can be told from these new results doesn't change so much: with improvements in the academic achievements, that are practically impossible to achieve, there is no significant reduction of the wage gaps between school types.

## 6.4 Quantile Regressions

Continuing with a deepening of our results we will evaluate if there is a differentiated effect in the different percentiles of income. This exercise can provide valuable information to understand where there are greater wage gaps in the distribution and where the Endowment Effect would have a greater impact.

The linear regressions we developed in our article estimates how, on average, the test score obtained by the individuals affect their future wages. While this model can address the question “how important are the academic achievements to explain future wages?” it cannot answer the important question: “does the academic achievements influence future wages differently for the individuals who earn low wages than for those who earn high wages?”

We use the quantile regression methodology for a more comprehensive picture of the effect of the math SIMCE on future wages.

This methodology models the relation between a set of predictor variables and specific quantiles of the response variable and it is useful when there are atypical values in the dependent variable so that some percentiles of the wage distribution may be more affected by their test score.19

We estimated the equation (3), using the three different specifications previously developed, but evaluated in the 20th, 40th, 60th, and 80th percentiles. As wages are positively skewed with a very long right tail, and the mean of the wages is higher than the median, we expect an overestimation of the return on wages for the individuals who earn lower wages and therefore the Endowment Effect would be overestimated for them.

Table 12: Statistics of the wages distribution by school type

| | Median | Mean |
|---|---|---|
| Public | 596.1 | 727.6 |
| Private-Voucher | 644.5 | 776.5 |
| Private-fee-paying | 783.2 | 986.5 |

Notes: This table summarizes the results of the Endowment Effect when using the different returns on wages of the math test score derived from the different specifications.

By developing this new methodology there are two main facts to highlight. Firstly, we can see that in the lower percentiles there is a lower wage gap by school type. In the 20th percentile the wages earned by the individuals educated in public schools represent a 78% of the wages earned by the individuals from private-fee-paying schools, while in the 80th this percentage is only a 72%. And secondly, the return on wages of the math test score is higher for the highest income percentiles. Therefore, our final results show that the Endowment Effect is higher for the percentiles 60th, and 80th, but the wage gap is still higher when evaluating in those tranches of the distribution.

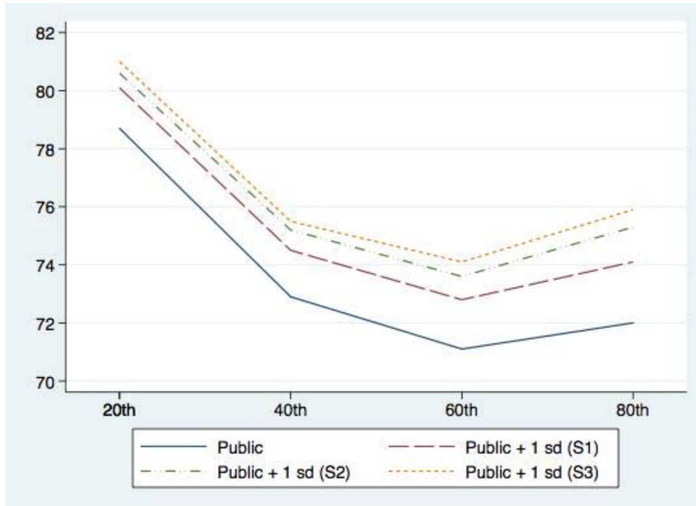
This result is still very unpromising because those individuals who come from public funded schools that have higher academic achievements would have higher wage gaps with respect their peers who educated in private-fee-paying schools.

Table 13: Return on wages of the math SIMCE by specification and quantile

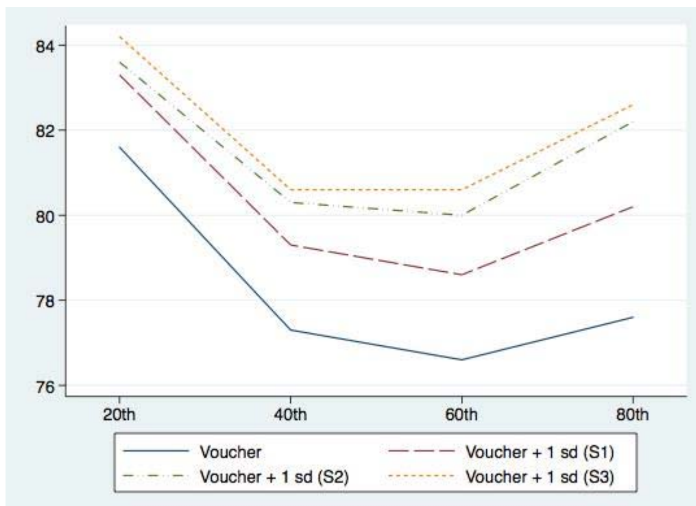
| | **Linear Regression** | **Quantile Regression 20th** | **40th** | **60th** | **80th** |
|---|---|---|---|---|---|
| Public S1 | 0.000479 | 0,0003169 | 0,0003911 | 0,0004323 | 0,0005095 |
| Public S2 | 0.000695 | 0,0004379 | 0,0005379 | 0,0006189 | 0,0007974 |
| Public S3 | 0.000815 | 0,0005234 | 0,0006271 | 0,0007571 | 0,0009559 |
| Voucher S1 | 0.000506 | 0,0003555 | 0,0004545 | 0,0004579 | 0,0005869 |
| Voucher S2 | 0.000797 | 0,0004304 | 0,0006854 | 0,0007832 | 0,0010205 |
| Voucher S3 | 0.000890 | 0,0005586 | 0,0007378 | 0,0009263 | 0,0011148 |

Notes: this table summarizes the return on wages of the math test score obtained with the different specifications and quantiles. S1 corresponds to the first specification. S2 corresponds to the second specification. S3 corresponds to the third specification. All these coefficients are statistically significant at 99% confidence interval.

Figure 3: Endowment Effect by quantile
(Percentage of private-fee-paying wages)




(a) Public Schools




(b) Private-Voucher Schools

## 7. Concluding Remarks

We explore the wage gap between school types in Chile, a high-income country with high levels of inequality, by taking advantage of a rich longitudinal database that links the last years of education with the first years at labor market of 103,424 individuals.

The inequality between school types in Chile has extensively been documented and the evidence indicates that Chilean education is not only not helping to reduce the initial gaps but rather is increasing and perpetuating them.

Following Bourguignon, Fournier & Gurgand (2001) we applied a decomposition method in order to decompose wages in its determinants for the three groups of students: the ones who studied in private-fee-paying, private-vouchers, and public schools.

Using that methodology and by simulating changes in the returns and in the level of endowments of the academic achievements, we tried to answer whether it is possible or not for the individuals that comes from a public funded school to close the existent wage gaps maintained with their peers from private-fee-paying school.

Despite the same methodology has been applied for the Chilean case by many authors, our work differs from what has already been done for two reasons. Firstly, instead of analyzing data at household levels, we can look at wages differentials at the individual level, so we can capture individual level heterogeneity which is very important when analyzing wage differentials. Secondly, as we use a longitudinal data, we estimate wages controlling for previous variables such as the academic achievement, the school attendance and some familiar characteristics reported by parents at the last years in school. Therefore, we can eliminate the effect of the non-observable that would affect our estimates if we have used cross sectional data. Both differences result in more accurate estimations of the parameters used to simulate trajectories and thus, in more reliable conclusions.

We develop two types of simulations in which we modify some parameters for the individuals educated in public funded schools, in order to observe how their wages trajectories converge towards the level of wages earned by individuals educated in private-fee-paying schools. The first one, the Endowment Effect, quantifies the impact on wages that would have had a change in the test score obtained at 2003, keeping prices constant. The second one, the Price Effect, quantifies the impact on wages that would have had a change in the prices associated to the test score, keeping the endowments constant.

Our results are discouraging. Even when simulating enormous changes in the academic achievements of the individuals, there is a considerable difference in the endowment returns between school types that makes the existent wage gap irrevocable.

Different public policies that have sought to improve the academic performance of students have succeeded in increasing academic outputs at most in 0.26 standard deviations. Our simulations shows us that, given the prices at labor market, there would be required at least 6.99 extra standard deviations in SIMCE to close the wage gap between private-vouchers and private-fee-paying students at 2012 and 9.57 extra standard deviations for the ones that studied in public schools.

These conclusions are aligned with Contreras, Rodriguez & Urzúa (2015): they state that in order to achieve a significant reduction on income inequality, the human capital investment on low-achievement students has to exceed -by far- the associated investment for ablest students. Furthermore, our results allow us to state that as long as the differences in returns by school type remains stable, no public policy neither major investment e orts will eliminate the wage differentials.

This paper is an urgent reminder to mind the gap.

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# 9. Appendix

Table 14: Descriptive Statistics: Family and individual characteristics

| Variable | Mean | Std. Dev. | Obs. |
|---|---|---|---|
| **Individual Characteristics** | | | |
| Men | 0.556 | 0.497 | 103,424 |
| Age | 24913 | 0.804 | 103,424 |
| Urban Zone | 0.827 | 0.378 | 103,424 |
| Years of Schooling after Simce | 4741 | 2.01 | 103,424 |
| Finish Secondary Education | 0.882 | 0.322 | 103,424 |
| Finish Tertiary Education | 0.106 | 0.308 | 103,424 |
| **Family Characteristics** | | | |
| Family Income I (w<$434) | 0.801 | 0.399 | 103,424 |
| Family Income II ($434<w<$868) | 0.132 | 0.338 | 103,424 |
| Family Income III ($868<w<$1,446) | 0.035 | 0.184 | 103,424 |
| Family Income IV ($1,446<w<$2,025) | 0.011 | 0.105 | 103,424 |
| Family Income V ($2,025<w<$2,603) | 0.006 | 0.079 | 103,424 |
| Family Income VI ($2,603<w) | 0.015 | 0.121 | 103,424 |
| Mother`s Ed.: primary | 0.399 | 0.49 | 103,424 |
| Mother`s Ed.: secondary | 0.362 | 0.481 | 103,424 |
| Mother`s Ed.: secondary vocational | 0.125 | 0.331 | 103,424 |
| Mother`s Ed.: technical institute (undergrad.) | 0.025 | 0.156 | 103,424 |
| Mother`s Ed.: professional institute (grad.) | 0.036 | 0.185 | 103,424 |
| Mother`s Ed.: university (undergrad.) | 0.046 | 0.21 | 103,424 |
| Mother`s Ed.: university (grad.) | 0.005 | 0.068 | 103,424 |
| Father`s Ed.: primary | 0.353 | 0.478 | 103,424 |
| Father`s Ed.: secondary | 0.383 | 0.486 | 103,424 |
| Father`s Ed.: secondary vocational | 0.135 | 0.342 | 103,424 |
| Father`s Ed.: technical institute (undergrad.) | 0.025 | 0.155 | 103,424 |
| Father`s Ed.: professional institute (grad.) | 0.031 | 0.174 | 103,424 |
| Father`s Ed.: university (undergrad.) | 0.062 | 0.241 | 103,424 |
| Father`s Ed.: university (grad.) | 0.007 | 0.085 | 103,424 |
| Books | 0.22 | 0.414 | 103,424 |
| High Expectations | 0.406 | 0.491 | 103,424 |

Notes: Years of schooling are the years after SIMCE in which the student went to secondary or tertiary education. Books represent the percentage of households with more than 100 books available at 2003. High expectations represent percentage of parents who believed, in 2003, their children would complete higher education at university.

Table 15: Descriptive statistics of education and labor market

| Variable | Mean | Std. Dev. | Obs. |
|---|---|---|---|
| **Educational characteristics** | | | |
| Public | 0.492 | 0.5 | 103,424 |
| Private-vouchers | 0.398 | 0.49 | 103,424 |
| Private-fee-paying | 0.11 | 0.313 | 103,424 |
| School grades (2003) | 5,381 | 0.604 | 103,424 |
| School attendance (% 2003) | 93,044 | 8,630 | 103,424 |
| Language SIMCE | 247.22 | 47.67 | 103,424 |
| Math SIMCE | 239.86 | 55.94 | 103,424 |
| Professional Institute | 0.077 | 0.267 | 103,424 |
| Technical Training Centers | 0.142 | 0.349 | 103,424 |
| Private university | 0.114 | 0.317 | 103,424 |
| CRUCh university | 0.101 | 0.301 | 103,424 |
| **Labor characteristics** | | | |
| Wage 2012 | 775.58 | 527.32 | 103,424 |
| Experience in months (up to 2012) | 40646 | 23468 | 103,424 |
| Indefinite contract | 0.634 | 0.482 | 103,424 |
| **Distribution of the sample according to economic activity** | | | |
| Agriculture, livestock, hunting and forestry | 0.046 | 0.209 | 103,424 |
| Fishing | 0.005 | 0.072 | 103,424 |
| Mine exploitation | 0.013 | 0.112 | 103,424 |
| Non-Metallic Manufacturing | 0.073 | 0.261 | 103,424 |
| Metallic Manufacturing | 0.031 | 0.173 | 103,424 |
| Electricity, gas and water supply | 0.004 | 0.06 | 103,424 |
| Construction | 0.099 | 0.298 | 103,424 |
| Commerce | 0.2 | 0.4 | 103,424 |
| Hotels and restaurants | 0.052 | 0.223 | 103,424 |
| Transportation and communications | 0.063 | 0.242 | 103,424 |
| Financial intermediation | 0.028 | 0.165 | 103,424 |
| Real estate and business activities | 0.184 | 0.388 | 103,424 |
| Public administration and defense | 0.017 | 0.13 | 103,424 |
| Teaching | 0.057 | 0.232 | 103,424 |
| Social and Health Services | 0.027 | 0.161 | 103,424 |
| Service activities | 0.064 | 0.245 | 103,424 |
| Building and Condominium Management | 0.002 | 0.041 | 103,424 |
| Extraterritorial organizations | 0.0002 | 0.014 | 103,424 |
| Not Specified Activity | 0.037 | 0.189 | 103,424 |

Note: the wages variables are expressed in US dollars.

Table 16: Average monthly wages by group and economic activity

| Economic activity | Public | | Private-Vouchers | | Private-fee-paying | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Mine exploitation | 839324 | 490306 | 8062,17 | 518628 | 1022064 | 574109 |
| Electricity, gas and water supply | 519108 | 339221 | 567478 | 303,98 | 617826 | 343938 |
| Financial intermediation | 457103 | 258312 | 538382 | 318617 | 766448 | 442079 |
| Social and Health Services | 435036 | 294414 | 487644 | 320571 | 595324 | 421973 |
| Metallic Manufacturing | 423607 | 247461 | 415443 | 242162 | 481585 | 269613 |
| Teaching | 401719 | 225648 | 419285 | 227,86 | 485444 | 257541 |
| Construction | 399276 | 233519 | 405056 | 244,26 | 472207 | 288104 |
| Fishing | 398022 | 212487 | 438133 | 215,8 | 375717 | 339137 |
| Transportation and communications | 366754 | 206588 | 407794 | 232998 | 542557 | 363515 |
| Non-Metallic Manufacturing | 368341 | 199746 | 398984 | 237159 | 514,71 | 311308 |
| Not Speci ed Activity | 364319 | 259609 | 371331 | 262619 | 436389 | 322415 |
| Real estate and business activities | 350956 | 232,52 | 362107 | 239309 | 476,91 | 343613 |
| Commerce | 320886 | 203,73 | 346,12 | 220794 | 446355 | 314822 |
| Service activities | 299219 | 205372 | 341649 | 234,28 | 415578 | 291983 |
| Extraterritorial organizations | 364145 | 186601 | 263504 | 183,94 | 382329 | 81919 |
| Public administration and defense | 289206 | 151472 | 329338 | 199,41 | 354854 | 231945 |
| Agriculture, livestock, hunting and forestry | 244461 | 149751 | 289531 | 197179 | 354133 | 277558 |
| Hotels y restaurants | 260029 | 140955 | 255784 | 145226 | 274401 | 192186 |
| Building and Condominium Management | 240292 | 91029 | 235913 | 101694 | 234,77 | 88925 |
| Total | 354,58 | 236,156 | 378,53 | 249,617 | 480,567 | 339,029 |

Table 17: Educational Programs Effect

| Paper | Program | Country | Results |
|---|---|---|---|
| Bellei (2009): Does Lengthening the school day increases student academic achievement? Results from a Natural Experiment in Chile. | JEC | Chile | 0.05-0.07 SD in Language SIMCE and 0.00-0.12 SD in Math SIMCE, where 0.07 is the most convincing estimate according to the author. |
| Hsieh y Urquiola (2006) The effects of generalized school choice on achievement and stratification. Evidence from Chile`s voucher program. | Vouchers | Chile | -0.012/-0.22 SD in math SIMCE and -0.05/-015 SD in Language Simce. |
| Contreras y Rau (2012): Tournament incentives for teachers, Evidence from a scaled up intervention in Chile. | SNED | Chile | 0.14-0.26 SD in Language SIMCE and 0.016-0.25 SD in Math SIMCE. |
| Santibañez (2005):Why should we care if teachers get A's: Teacher test scores and student achievement in Mexico. | Carrera Magisterial | México | 1 SD in the teacher score raises primary student performance in 0.08 SD and secondary student performance in 0.25 SD. |
| Agüero y Beleche (2013): Test-Mex: Estimating the effects of school year length on student performance in México. | Exogenous variation in the length of the School Year | México | Exogenous variation in the length of the School Year & Mexico & 10 more class day can improve ENLACE (National valuation of academic achievement in scholar centres) scores in 0.04-0.07 SD. |
| Krueger (1999): Experimental Estimates of Education Production functions. | STAR | USA | Effect on Stanford Achievement tests: 0.2 SD in Pre-Primary School, 0.28 SD in Primary school, 0.22 in secondary, 0.19 in tertiary. |
| Marcotte (2007) y Hansen (2008) | Exogenous variation in the length of the School Year | USA, Maryland | 10 less class days worsen math results in 0.15 SD. |
| Angrist et al (2000). Vouchers for private schooling in Colombia: Evidence from a randomized Natural Experiment. | PACE | Colombia | 0.153 SD in Math, 0.128 SD in writing and 0.203 in reading. Reading is the only statistically significant coefficient. |

Table 18: Characterization by school type for the graduates

| Variable | Public | | Private Voucher | | Private | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Math Simce | 265 | 53.65 | 274.8 | 51.11 | 306.6 | 54.76 |
| Language Simce | 270.2 | 44.35 | 277.8 | 42.18 | 294.2 | 42.57 |
| School Grades | 5.8 | 0.54 | 5.7 | 0.54 | 5.9 | 0.51 |
| Scholarship | 6.7 | 1.03 | 6.9 | 0.93 | 7.1 | 0.85 |
| Wages (2012) | 1070.9 | 617.18 | 1110.6 | 611.53 | 1462.6 | 802.04 |
| Observations | 3,837 | | 5,161 | | 1,986 | |

Table 19: Results for the regression for the public schools by Specification.

| VARIABLES | Specification 1 | Specification 2 | Specification 3 |
|---|---|---|---|
| | lnW | lnW | lnW |
| Math Simce | 0.000479*** | 0.000695*** | 0.000815*** |
| | (-0.0000692) | (-0.0000596) | (-0.0000604) |
| Language Simce | -0.0000384 | | |
| | (-0.0000702) | | |
| School grades | 0.0608*** | | |
| | (-0.00523) | | |
| Secondary education | 0.0375*** | 0.0578*** | |
| | (-0.00733) | (-0.00716) | |
| Tertiary education | 0.435*** | 0.442*** | |
| | (-0.0114) | (-0.0114) | |
| Family income | 0.0589*** | 0.0578*** | 0.0625*** |
| | (-0.00725) | (-0.00726) | (-0.0074) |
| Scholarship | 0.0237*** | 0.0244*** | 0.0359*** |
| | (-0.00227) | (-0.00227) | (-0.00221) |
| Constant | 4.841*** | 4.786*** | 4.560*** |
| | (-1.252) | (-1.251) | (-1.263) |
| Observations | 50845 | 50845 | 50845 |
| R-squared | 0.296 | 0.294 | 0.266 |
| Other control variables | Yes | Yes | Yes |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 20: Results for the regression for the private-vouchers schools by Specification.

| VARIABLES | Specification 1<br>lnW | Specification 2<br>lnW | Specification 3<br>lnW |
|---|---|---|---|
| Math Simce | 0.000506*** | 0.000797*** | 0.000890*** |
| | (-0.0000786) | (-0.0000669) | (-0.0000683) |
| Language Simce | -0.00013 | | |
| | (-0.0000829) | | |
| School grades | 0.0844*** | | |
| | (-0.00605) | | |
| Secondary education | 0.0189** | 0.0431*** | |
| | (-0.00929) | (-0.00912) | |
| Tertiary education | 0.434*** | 0.443*** | |
| | (-0.00991) | (-0.00992) | |
| Family income | 0.0503*** | 0.0498*** | 0.0528*** |
| | (-0.00525) | (-0.00528) | (-0.00546) |
| Scholarship | 0.0218*** | 0.0229*** | 0.0308*** |
| | (-0.00245) | (-0.00246) | (-0.00244) |
| Constant | 9.075*** | 8.611*** | 8.776*** |
| | (-1.519) | (-1.525) | (-1.55) |
| Observations | 41178 | 41178 | 41178 |
| R-squared | 0.264 | 0.261 | 0.22 |
| Individual Characteristics | Yes | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Familiar Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 21: Results of regressions for the 20th quartil

| VARIABLES | (1) Public | (2) Voucher | (3) Private |
|---|---|---|---|
| Math Simce | 0.000317*** | 0.000355*** | 0.000685*** |
| | (-0.0000975) | (-0.000117) | (-0.000257) |
| Language Simce | 0.0000551 | -0.000221* | -0.000319 |
| | (-0.000101) | (-0.000123) | (-0.000272) |
| School grades | 0.0292*** | 0.0473*** | 0.0925*** |
| | (-0.00752) | (-0.00914) | (-0.0201) |
| Secondary education | 0.0649*** | 0.0449*** | 0.0991* |
| | (-0.0114) | (-0.0159) | (-0.0522) |
| Tertiary education | 0.435*** | 0.501*** | 0.548*** |
| | (-0.0144) | (-0.0138) | (-0.0267) |
| Family Income | 0.0400*** | 0.0343*** | 0.0821*** |
| | (-0.00886) | (-0.00697) | (-0.00928) |
| Scholarship | 0.0117*** | 0.0110*** | 0.0156* |
| | (-0.00322) | (-0.00373) | (-0.0083) |
| Constant | 4.492** | 6.241** | 3.222 |
| | (-1900) | (-2431) | (-7253) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Familiar Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22: Results of regressions for the 40th quartil

| VARIABLES | (1) Public | (2) Voucher | (3) Private |
|---|---|---|---|
| Math Simce | 0.000391*** | 0.000454*** | 0.000931*** |
| | (-0.0000768) | (-0.0000955) | (-0.000208) |
| Language Simce | -0.0000942 | -0.0000579 | -0.000461** |
| | (-0.0000799) | (-0.0001) | (-0.00022) |
| School grades | 0.0507*** | 0.0616*** | 0.102*** |
| | (-0.00593) | (-0.00745) | (-0.0162) |
| Secondary education | 0.0491*** | 0.0346*** | 0.0823* |
| | (-0.009) | (-0.013) | (-0.0421) |
| Tertiary education | 0.453*** | 0.452*** | 0.440*** |
| | (-0.0113) | (-0.0113) | (-0.0215) |
| Family Income | 0.0472*** | 0.0421*** | 0.0878*** |
| | (-0.00698) | (-0.00569) | (-0.00749) |
| Scholarship | 0.0176*** | 0.0201*** | 0.0168** |
| | (-0.00254) | (-0.00304) | (-0.0067) |
| Constant | 3.998*** | 8.244*** | -1.958 |
| | (-1496) | (-1983) | (-5854) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Familiar Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23: Results of regressions for the 60th quartil

| VARIABLES | (1)<br>Public | (2)<br>Voucher | (3)<br>Private |
|---|---|---|---|
| Math Simce | 0.000432*** | 0.000458*** | 0.000971*** |
| | (-0.0000749) | (-0.0000871) | (-0.000179) |
| Language Simce | -0.0000777 | 0.0000263 | -0.000398** |
| | (-0.0000779) | (-0.0000915) | (-0.000189) |
| School grades | 0.0597*** | 0.0871*** | 0.117*** |
| | (-0.00578) | (-0.0068) | (-0.014) |
| Secondary education | 0.0239*** | 0.0249** | 0.0805** |
| | (-0.00878) | (-0.0118) | (-0.0362) |
| Tertiary education | 0.439*** | 0.424*** | 0.293*** |
| | (-0.0111) | (-0.0103) | (-0.0185) |
| Family Income | 0.0661*** | 0.0488*** | 0.0791*** |
| | (-0.00681) | (-0.00519) | (-0.00644) |
| Scholarship | 0.0267*** | 0.0312*** | 0.0296*** |
| | (-0.00248) | (-0.00277) | (-0.00576) |
| Constant | 4.402*** | 7.252*** | -0.536 |
| | (-1461) | (-1808) | (-5035) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Familiar Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: Results of regressions for the 80th quartil

| VARIABLES | (1)<br>Public | (2)<br>Voucher | (3)<br>Private |
|---|---|---|---|
| Math Simce | 0.000432*** | 0.000458*** | 0.000971*** |
| | (-0.0000749) | (-0.0000871) | (-0.000179) |
| Language Simce | -0.0000777 | 0.0000263 | -0.000398** |
| | (-0.0000779) | (-0.0000915) | (-0.000189) |
| School grades | 0.0597*** | 0.0871*** | 0.117*** |
| | (-0.00578) | (-0.0068) | (-0.014) |
| Secondary education | 0.0239*** | 0.0249** | 0.0805** |
| | (-0.00878) | (-0.0118) | (-0.0362) |
| Tertiary education | 0.439*** | 0.424*** | 0.293*** |
| | (-0.0111) | (-0.0103) | (-0.0185) |
| Family Income | 0.0661*** | 0.0488*** | 0.0791*** |
| | (-0.00681) | (-0.00519) | (-0.00644) |
| Scholarship | 0.0267*** | 0.0312*** | 0.0296*** |
| | (-0.00248) | (-0.00277) | (-0.00576) |
| Constant | 4.402*** | 7.252*** | -0.536 |
| | (-1461) | (-1808) | (-5035) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Familiar Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Results of the Endowment Effect 20th Quartile. Specification (2).

| VARIABLES | Public<br>lnd12 | Private-voucher<br>lnd12 | Private-fee-paying<br>lnd12 |
|---|---|---|---|
| Math Simce | 0.000438*** | 0.000430*** | 0.000829*** |
| | (-0.0000852) | (-0.0000992) | (-0.000225) |
| Secondary education | 0.0756*** | 0.0532*** | 0.142*** |
| | (-0.0114) | (-0.0157) | (-0.0532) |
| Tertiary education | 0.439*** | 0.503*** | 0.567*** |
| | (-0.0147) | (-0.0138) | (-0.0274) |
| Family Income | 0.0406*** | 0.0338*** | 0.0795*** |
| | (-0.00907) | (-0.00699) | (-0.00955) |
| Scholarship | 0.0105*** | 0.0101*** | 0.0149* |
| | (-0.0033) | (-0.00374) | (-0.00855) |
| Constant | 4.203** | 5.697** | 1.259 |
| | (-1.945) | (-2.436) | (-7.474) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 26: Results of the Endowment Effect 40th Quartile. Specification (2).

| VARIABLES | Public<br>lnd12 | Private-voucher<br>lnd12 | Private-fee-paying<br>lnd12 |
|---|---|---|---|
| Math Simce | 0.000538*** | 0.000685*** | 0.00119*** |
| | (-0.0000666) | (-0.0000811) | (-0.000175) |
| Secondary education | 0.0631*** | 0.0542*** | 0.116*** |
| | (-0.00892) | (-0.0128) | (-0.0413) |
| Tertiary education | 0.460*** | 0.458*** | 0.463*** |
| | (-0.0115) | (-0.0113) | (-0.0213) |
| Family Income | 0.0463*** | 0.0413*** | 0.0862*** |
| | (-0.00709) | (-0.00572) | (-0.00742) |
| Scholarship | 0.0177*** | 0.0210*** | 0.0162** |
| | (-0.00258) | (-0.00306) | (-0.00664) |
| Constant | 3.504** | 7.807*** | -3.2 |
| | (-1.521) | (-1.994) | (-5.803) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 27: Results of the Endowment Effect 60th Quartile. Specification (2).

| VARIABLES | Public<br>lnd12 | Private-voucher<br>lnd12 | Private-fee-paying<br>lnd12 |
|---|---|---|---|
| Math Simce | 0.000619*** | 0.000783*** | 0.00124*** |
| | (-0.0000645) | (-0.0000739) | (-0.000154) |
| Secondary education | 0.0429*** | 0.0440*** | 0.106*** |
| | (-0.00864) | (-0.0117) | (-0.0363) |
| Tertiary education | 0.451*** | 0.436*** | 0.308*** |
| | (-0.0111) | (-0.0103) | (-0.0187) |
| Family Income | 0.0641*** | 0.0488*** | 0.0826*** |
| | (-0.00687) | (-0.00521) | (-0.00652) |
| Scholarship | 0.0281*** | 0.0343*** | 0.0360*** |
| | (-0.0025) | (-0.00279) | (-0.00584) |
| Constant | 3.482** | 7.090*** | -1.511 |
| | (-1.472) | (-1.817) | (-5.103) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 28: Results of the Endowment Effect 80th Quartile. Specification (2).

| VARIABLES | Public<br>lnd12 | Private-voucher<br>lnd12 | Private-fee-paying<br>lnd12 |
|---|---|---|---|
| Math Simce | 0.000797*** | 0.00102*** | 0.00121*** |
| | (-0.0000773) | (-0.0000839) | (-0.000163) |
| Secondary education | 0.0517*** | 0.0402*** | 0.0592 |
| | (-0.0104) | (-0.0133) | (-0.0385) |
| Tertiary education | 0.406*** | 0.378*** | 0.236*** |
| | (-0.0133) | (-0.0117) | (-0.0198) |
| Family Income | 0.0686*** | 0.0531*** | 0.0604*** |
| | (-0.00824) | (-0.00592) | (-0.00692) |
| Scholarship | 0.0365*** | 0.0388*** | 0.0442*** |
| | (-0.003) | (-0.00316) | (-0.0062) |
| Constant | 3.592** | 9.044*** | 1.216 |
| | (-1.766) | (-2.062) | (-5.417) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 29: Results of the Endowment Effect 20th Quartile. Specification (3).

| VARIABLES | Public | Private-voucher | Private-fee-paying |
|---|---|---|---|
| | lnd12 | lnd12 | lnd12 |
| Math Simce | 0.000523*** | 0.000559*** | 0.00102*** |
| | (-0.0000823) | (-0.0000984) | (-0.000223) |
| Family Income | 0.0462*** | 0.0364*** | 0.102*** |
| | (-0.00879) | (-0.00697) | (-0.00945) |
| Scholarship | 0.0262*** | 0.0216*** | 0.0322*** |
| | (-0.00307) | (-0.00362) | (-0.00829) |
| Constant | 4.700** | 5.806** | 1.374 |
| | (-1.884) | (-2.42) | (-7.372) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 30: Results of the Endowment Effect 40th Quartile. Specification (3)

| VARIABLES | Public<br>lnd12 | Private-voucher<br>lnd12 | Private-fee-paying<br>lnd12 |
|---|---|---|---|
| Math Simce | 0.000627*** | 0.000738*** | 0.00121*** |
| | (-0.0000678) | (-0.0000798) | (-0.000174) |
| Family Income | 0.0513*** | 0.0434*** | 0.0971*** |
| | (-0.00725) | (-0.00564) | (-0.00738) |
| Scholarship | 0.0302*** | 0.0327*** | 0.0319*** |
| | (-0.00253) | (-0.00293) | (-0.00647) |
| Constant | 3.728** | 8.545*** | -2.657 |
| | (-1.553) | (-1.961) | (-5.754) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 31: Results of the Endowment Effect 60th Quartile. Specification (3)

| VARIABLES | Public<br>lnd12 | Private-voucher<br>lnd12 | Private-fee-paying<br>lnd12 |
|---|---|---|---|
| Math Simce | 0.000757*** | 0.000926*** | 0.00132*** |
| | (-0.0000661) | (-0.0000774) | (-0.000145) |
| Family Income | 0.0682*** | 0.0491*** | 0.0852*** |
| | (-0.00707) | (-0.00548) | (-0.00615) |
| Scholarship | 0.0394*** | 0.0436*** | 0.0482*** |
| | (-0.00247) | (-0.00285) | (-0.00539) |
| Constant | 3.329** | 8.072*** | -4.129 |
| | (-1.514) | (-1.904) | (-4.794) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 32: Results of the Endowment Effect 80th Quartile. Specification (3)

| VARIABLES | Public | Private-voucher | Private-fee-paying |
|---|---|---|---|
| | lnd12 | lnd12 | lnd12 |
| Math Simce | 0.000956*** | 0.00111*** | 0.00121*** |
| | (-0.0000736) | (-0.0000842) | (-0.000164) |
| Family Income | 0.0833*** | 0.0606*** | 0.0575*** |
| | (-0.00787) | (-0.00596) | (-0.00693) |
| Scholarship | 0.0462*** | 0.0455*** | 0.0465*** |
| | (-0.00274) | (-0.0031) | (-0.00608) |
| Constant | 3.474** | 8.563*** | 2.967 |
| | (-1.685) | (-2.07) | (-5.404) |
| Observations | 50,845 | 41,178 | 11,401 |
| Individual Characteristics | YES | YES | YES |
| Educational Characteristics | YES | YES | YES |
| Family Characteristics | YES | YES | YES |
| Economic Activity | YES | YES | YES |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 4: Distribution of 2012 wages by school type