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This paper is a draft submission to

Inequality—Measurement, trends, impacts, and policies

5–6 September 2014 Helsinki, Finland

This is a draft version of a conference paper submitted for presentation at UNU-WIDER's conference, held in Helsinki on 5–6 September 2014. This is not a formal publication of UNU-WIDER and may reflect work-in-progress.

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On the Origins of Inequality in Chile*

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First draft: January 16, 2012

This version: April 23, 2014

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Abstract

This paper explores the role of early human capital endowments and the education system as determinants of labor market outcomes in Chile. We pay particular attention to income inequality, which has been historically high and stable in this country. Specifically, using reduced-form models we investigate how individual- and school-level variables shape the dispersion of labor income. Our empirical strategy uses unique longitudinal data combining administrative information on individual-level test scores in high school (2001), school and family characteristics, as well as adult earnings (2011). We show that high school types (public, private-voucher or private-fee-paying, as well as for- and non-for profit schools) are important sources of earnings heterogeneity. Specifically, we document that private-fee-paying schools have a greater return on earnings than voucher and public schools. This result emerges even after controlling for individual academic achievement. The data also allows us to analyze the impact of two major educational reforms implemented in Chile during the 90s: A teacher incentive program providing monetary rewards to high-achieving schools in a tournament framework and a program lengthening the school day. Both policies have positive effects, but only for ablest students in private-voucher and private-fee-paying schools. Finally, we show that educational (public and private) investment at age 16 has greater effects on earnings for students in private-fee-paying schools. The results illustrate how the educational system can perpetuate and contribute to income inequality.

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Keywords: Education policy, income inequality, labor market outcomes

JEL codes: I24, J24

1 Introduction

Despite the rapid growth of Chile during the last two decades, income inequality has shown a remarkable stability. Although during recent years different indicators have documented a small improvement in inequality, it still remains high compared to OECD economies.¹

There is a vast literature analyzing the sources of this high inequality. Most of the studies approach income inequality analysis using cross-sectional data (Cowan and De Gregorio, 1996; Bravo and Marinovic, 1997; Contreras and Ruiz-Tagle, 1997; Contreras, 1998; Bravo, Contreras, and Rau, 1999; Ruiz-Tagle, 1999; Contreras, Larrañaga, Litchfield, and Valdés, 2001; Bravo, Contreras, and Urzúa, 2002; Contreras, 2002). Particularly, based on cohorts analysis, Contreras (1998), Bravo, Contreras, and Urzúa (2002) and Contreras (2002) find an important role for education in explaining wage inequality. Although cross-sectional analysis provides relevant insights to the study of inequality, it neglects other individual-level mechanisms that can explain income inequality. Some of these mechanisms are associated to decisions that occur at early ages. Cross-sectional analysis does not reveal the linkages between early education and adult wage heterogeneity.

In this paper, we explore the effect of individuals' pre-labor market characteristics and early circumstances on income inequality using longitudinal data for Chile, a high-inequality economy. We posit a variety of reduced-form models that allow us to estimate the effect of several aspects of the educational system on students' earnings heterogeneity. We explore the impact on future earnings of different types of schools (private, public or for-profit with different funding systems). Furthermore, we analyze the effect of academic achievement on earnings and explore the heterogeneity of this return across different schooling institutions.

¹The GINI coefficient (after taxes and transfers) for Chile equals 0.503, whereas the OECD average is 0.316 (source: OECD).

We also study the effectiveness of major educational public policies in helping to reduce inequality. Finally, we assess the role of private and public educational investments on earnings differentials.

Our approach follows closely the literature that emphasizes the importance of early educational investments.² However, our main contribution consists in quantifying the impact of the interaction of the educational system and educational public policies with individuals' pre-labor market endowments on earnings heterogeneity.

Our regression analysis uses administrative records of standardized test scores measuring language and math skills of 10th graders. We have rich information about students' families, school and families' education-related expenditures. We complement our data with administrative records on future labor market outcomes from the same cohort of students 10 years later. This is the first paper linking data on individual's schooling achievement and adult labor market performance for Chile.

Our main results are:

1. We find a significant association between high school types and earnings. We show that studying in a private-fee-paying school is associated with a 13% increase on monthly earnings over studying in a public school, after we control for individual exogenous characteristics, family socioeconomic background and academic achievement. On the other hand, the same estimates show that attending private-voucher schools instead of public schools predicts an increase of 2% on earnings. Compared to private-voucher-for-profit, private-voucher-nonprofit schools increase earnings by 9%. Private-voucher with shared funding schemes (the tuition is paid by the parents and the Government through vouchers) have a 4% earning differential with respect to private-voucher-nonshared-funding schools.

²See [Heckman and Masterov \(2007\)](#) for a review on this issue, [Chetty, Friedman, Hilger, Saez, Schanzenbach, and Yaga \(2011\)](#) for an example of the impact of early education on adult outcomes and [Chetty, Friedman, and Rockoff \(2011\)](#) for an example of the effect of teacher value-added and student outcomes in adulthood.

2. We document a positive and significant effect of academic achievement on future earnings. An increase of one standard deviation in math and in language test score has an average return on earnings of 14% and 2%, respectively. Moreover, the marginal effect of academic achievement on earnings is increasing with the level of test scores. However, the labor market premium for academic achievement is substantially greater in private-fee-paying schools than in private-voucher and public schools.
3. The school average achievement (an approximation of what we could consider school quality) has also long-term effects on students' future labor income. Nonetheless, this effect is much stronger among students in private-fee-paying schools.
4. We study the effect of two national educational policies implemented at the time our studied cohort was attending high school. The first program (JEC) is directed to increase the hours that children spend in school. The second program (SNED) provides monetary incentives depending on teacher and overall school performance within a tournament framework. Both public policies were implemented at a national level, although SNED applies only to public and private-voucher schools. Our estimates indicate that JEC has positive long term effects on students' future earnings, but only for students attending private-fee-paying schools. On the other hand, the SNED program is related to higher labor market rewards only for individuals studying in private-voucher schools that have consistently won SNED tournament.
5. We measure private and public educational investment in adolescent years. We show that investment in educational resources has a positive and significant effect on future earnings. Nonetheless, this estimated impact is greater for students attending private-fee-paying schools than for students in public or private-voucher schools.

In sum, we show that earnings differentials can be partly explained from the interaction with students' human capital with different features of the schooling system. This interaction effect causes an increase in earnings inequality relative to the human capital gap present in

schooling years. This posits remarkable challenges to educational public policies directed to reduce income gaps in high-inequality economies such as Chile.

Our paper is structured in the following way. Section 2 describes the Chilean educational system and some public policies aiming at improving student's academic achievement. Section 3 reviews some preliminary data about different factors that may affect earnings inequality. Section 4 presents our empirical strategy. Section 5 details our data. Section 6 documents the results. Finally, section 7 concludes.

2 The Chilean Education System and Educational Policies

The Chilean educational system underwent significant modifications in the 1980s. The reforms included decentralizing the administration of educational establishments by transferring the administration of public schools from the Ministry of Education to Municipal Authorities. It also included a nationwide voucher system for both publicly and privately administered schools. The reform introduced a uniform demand-side subsidy in which parents are free to choose among the schools in the market.

As a result, education in Chile shifted to three kinds of administrative alternatives: public establishments funded by the student subsidy provided by the State and under municipal administration. Private-voucher establishments funded by the student subsidy and administered by the private sector, and private fee-paying establishments funded and administered by the private sector.³ The reform led to a sharp redistribution of the educational system, giving a strong push to the private subsidized sector. In fact, although approximately 15% of school admissions were private subsidized in 1981, by 2005 that figure had risen to 47%.

While private-voucher and public schools have the same funding program, there are some differences. Firstly, private-voucher schools can charge tuition since 1993, which is known

³Prior to the reform, there were already private subsidized schools, mainly belonging to non-profit religious institutions, with subsidies that were 50% of those given to public schools.

as the shared funding system. According to Ministry of Education data, in 2002, 90% of private subsidized schools received a co-payment from parents. Unlike voucher schemes implemented in other countries, private schools in Chile can choose their students. In the Netherlands, Belgium and Sweden, the private sector plays a significant role in education. However, those schools do not select students. For example, in Sweden, private schools must operate on the first-come, first-served basis, and cannot select students based on ability, income or ethnicity. Thus the Swedish private schools are consistently found on average to have similar socioeconomic composition compared with public schools (Sandström and Bergström, 2005), unlike Chile. In terms of impacts on learnings, the evidence is mixed (Sandström and Bergström, 2005; Bohlmark and Lindahl, 2008).

On the other hand, in Chile, public schools are prohibited for selecting students, except in cases where the demand for places exceeds availability. Lastly, private-voucher schools can exist as either for-profit or not-for-profit organizations.⁴

There are two major educational reforms, which took place around 1996 when the Chilean government announced a set of new initiatives designed to improve the quality of education. The measure that had the greatest impact on the school system was the implementation of the Full Schooling Day program (JEC as in Spanish acronym). This program consisted in extending the number of classroom hours by 30% annually without lengthening the school year. The change involved an average increase of 1.4 hours per school day. Prior to the reform, many schools had a double school day.⁵ The execution of the JEC program meant that those schools transitioned to a single school day format.⁶

The objectives of this program were to improve student learning and to increase equality in education. They were described as follows: “To contribute to the improvement of the

⁴While in 1981 most private subsidized schools belonged to religious institutions, after the reform most of the new schools were for-profit. For example, in 1988, 84% of new schools belonged to for-profit institutions (Hsieh and Urquiola, 2006).

⁵Under the old system, some students attended school in the morning while others attended in the afternoon.

⁶The reform led to a sharp redistribution of the educational system. The percentage of students in private-voucher schools increased from 15% in 1981 to 47% in 2005.

quality of education and provide equal learning opportunities for the boys, girls and adolescents throughout the country by significantly increasing teaching time in order to better develop the new curricular framework”. Thus, more time at school could positively affect learning, the technical work of teachers and the management of each school. Table 1 shows that students in JEC establishments have greater academic achievement and earnings. This unconditional evidence is consistent with Bellei (2009), which analyzes the effects of the increase in the length of the school day on academic performance in Chile. This study finds a positive and significant effect on academic performance in language and mathematics tests.

The second reform was the introduction of the only scaled-up teacher incentive program in the world. Since 1996, the Chilean Ministry of Education has incorporated a monetary based productivity bonus called The National System of School Performance Assessment (SNED). This is a rank-order tournament directed towards all public and private-voucher schools in the country, which represent 90% of enrolled students. The program is directed at all primary and/or secondary subsidized schools in the country and is financed by the government. Thus, the private fee-paying schools are excluded.

In the year 2000, 90% of all schools in Chile were public or private-voucher schools. The SNED, which is a supply side incentive, was created with two objectives. First, to improve educational quality provided by subsidized schools through monetary rewards to teachers. This strategy, defined as a pay-for-productivity wage compensation, seeks to change the fixed salary structure. The second objective was to provide the school community, parents, and those responsible for children with information on the educational progress of schools. It was expected that the school administrations and teachers would thus receive feedback on their teaching and administrative decisions

The program is a competitive system in which schools with similar characteristics are grouped into homogenous groups. The competition takes place within each distinct group. Thus, the SNED is a group incentive program in which schools compete on the basis of their average performance and monetary rewards are distributed equally among all teachers in the

winning schools.

The literature so far on SNED program suggests positive effects on academic performance. [Rau and Contreras \(2012\)](#) evaluate the effect of this tournament on SIMCE test score reporting significant results varying between 0.14 and 0.25 standard deviations for math and from 0.09 to 0.23 for language.

It must be noticed that previous evidence on JEC and SNED have been provided only for educational achievement and long-run effects on labor market outcomes have not been reported yet.

3 Wage Inequality in Chile and the Educational System

There are two basic facts about Chile's income distribution. The first one is that it is substantially higher compared with income inequality statistics for OECD economies (Figure 1). The second fact is that it has remained more or less stable over the last twenty years (although, it shows signs of modest improvement in the last decade), as Figure 2 shows. This persistence has led several authors to study its causes ([Cowan and De Gregorio, 1996](#); [Bravo and Marinovic, 1997](#); [Contreras and Ruiz-Tagle, 1997](#); [Contreras, 1998](#); [Bravo, Contreras, and Rau, 1999](#); [Ruiz-Tagle, 1999](#); [Contreras, Larrañaga, Litchfield, and Valdés, 2001](#); [Bravo, Contreras, and Urzúa, 2002](#); [Contreras, 2002](#)). Most of these papers have found that raising the average years of education was a fundamental factor for reducing wage inequality. Nonetheless, these analyses are based on cohort data from household surveys. Using these data, we can hardly explore in detail the specific mechanism linking human capital accumulation and earnings heterogeneity.

Our first approach to this problem is to focus into the role of the educational system and its long-term consequences. As we will explain later with greater detail, our sample consists in 10th graders in 2001. If we look at Table 2, it is evident that there are differences in

academic achievement between types of schools.^{7,8}

Given the evidence about the different effects of schools on academic achievement, it is expected that this academic added-value must have a reflection into the labor market. Consequently, Figure 3 shows that students in private-fee-paying schools have higher earnings than the rest of the schooling institutions. It also appears that there are significant differences between private-voucher and public schools. Figure 4 presents non-linear estimates on the relationship between academic achievement and earnings. Controlling for the short-term influence of schools (their effect on test-scores) we observe long-term impacts on earnings. Moreover, schools' earnings differentials depends on pre-labor market abilities approximated through math test score. The gap between private-voucher and public schools is relatively small and concentrated in the interval of 200 and 300 points.⁹ The gap between private-fee-paying schools and the rest of the schools type is also small in this last interval, but is strongly increasing with test scores. This evidence suggest that students in private-fee-paying schools have increasing gains to academic achievement. This non-linearity produces vast differences in earnings between schools for test scores above 300 points.¹⁰

Therefore, it seems that schools are playing a role in explaining future earning. But, what are the effects of the schooling system on earnings inequality? Table 4 shows the Theil inequality index coefficient of tests scores and earnings decomposed by school types. Several features of this evidence are worth to mention. First, inequality of test scores is less than the inequality of earnings. This imply that pre-labor market ability heterogeneity is not the sole factor that explains future outcomes. It could be the case that skills follow a divergent trend between students with high and low academic performance, given a positive relationship

⁷The sample used in this case is the same that we use in our regression analysis. For further information, check section 5.

⁸Several studies have analyzed returns on the academic achievement of these different schooling institutions (Carnoy and McEwan, 2000; McEwan, 2001; Carnoy and McEwan, 2003; Gallego, 2006; Contreras, Sepúlveda, and Bustos, 2010; Elacqua, Contreras, Salazar, and Santos, 2011). All papers coincide in that private-fee-paying schools have better academic performances, but the literature has not come to a clear consensus on the private-voucher and public schools comparison.

⁹The mean and standard deviation of Math test score is 247 and 52 points, respectively.

¹⁰Students with scores above 300 points represents 14% of total enrollment (see Table 3).

between the return of investing in human capital with skill level (Cunha, Heckman, Lochner, and Masterov, 2006; Cunha and Heckman, 2007, 2008). This element is enough to exacerbate the initial endowments' inequality. An interaction between other factors with skills could also explain the increasing inequality as students become older. This is the case illustrated in Figure 4, in which, given an initial inequality (see Table 2), further inequality is generated as students attend different high school institutions.

Second, although schooling could be a relevant factor for explaining earnings and academic achievement, there is a vast heterogeneity not fully accounted in these preliminary figures. Indeed, school type is a more relevant issue when one tries to explain test scores inequality than earnings inequality (see Table 4). Again, non-linearity and further interactions between school type and future human capital accumulation could perpetuate and increase inequality.

Intergenerational mobility is also a relevant factor. For instance, Table 5 documents that mothers' education could also explain inequality of earnings through the impact of current academic performance.

The figures in this section show us a preliminary approach of our inequality analysis. Our framework rests on the fact that wage inequality can be explained by early circumstances and, therefore, a cohort-analysis of inequality would show a very partial picture of how inequality is formed. Nonetheless, the numbers showed so far are just unconditional averages. In the next section we discuss identification issues.

4 The Empirical Approach

Our approach consists in setting up reduced-form linear regression models to account for the role of the individual's abilities, school characteristics, family background and educational policies at school age on earnings heterogeneity. Let us assume the traditional model of wages and education (Becker, 1962; Mincer, 1962; Card, 2001):

$$w_{i,\bar{t}} = C_i\alpha + E_{i,\underline{t}}\beta + \delta\theta_i + \epsilon_{i,\bar{t}} \quad (1)$$

where C_i are individual characteristics, $E_{i,t}$ are schooling variables and θ_i represents the individual's abilities. We observe log of wages ($w_{i,\bar{t}}$) at period \bar{t} and schooling variables from $t = 0 \dots \underline{t} < \bar{t}$. For the sake of simplicity, let schooling variables represented by the following linear model:

$$E_{i,t} = \lambda E_{i,t-1} + \kappa\theta_i + \phi C_i + v_{i,t}. \quad (2)$$

Note that $E_{i,t}$ could represent a dummy variable which equals 1 if the individual has a certain amount of years of schooling and 0 otherwise. If this is the case, (2) represents a linear probability model for schooling choices.

Our approach consists in analyzing early endowments (say, at $t = 0$) and its effects on the log of wages at $t = \bar{t}$. The reduced-form model relating labor market outcomes and early endowments can be obtained from equations (1) and (2):

$$w_{i,\bar{t}} = \beta\lambda^{\underline{t}}E_{i,0} + \theta_i(\delta + \beta\kappa \sum_{j=0}^{\underline{t}-1} \lambda^j) + C_i(\alpha + \beta\phi \sum_{j=0}^{\underline{t}-1} \lambda^j) + \tilde{\epsilon}_{i,\bar{t}}, \quad (3)$$

where $\tilde{\epsilon}_{i,\bar{t}} \equiv \epsilon_{i,\bar{t}} + \beta \sum_{j=0}^{\underline{t}-1} v_{i,\underline{t}-j} \lambda^j$.

Equation (3) shows that the effect of education at early ages ($t = 0$) can be calculated by estimating the composite parameter $\beta\lambda^{\underline{t}}$. Notice that this last term contains the direct impact of education on earnings, but also the impact of early educational interventions on subsequent schooling. The second and third term in equation (3) also shows direct and indirect effects of the individual's abilities and other characteristics on wages. We could

have modeled abilities in a similar fashion as with education in equation (2). If this is the case, reduced-form parameters would also include this indirect (and potentially important) effect. Identifying structural parameters in this case is not a trivial issue.¹¹ However, in this paper, we are not interested in pursuing this particular task. This means that we do not attempt to recover the specific mechanisms through which education affects subsequent earnings. For example, higher academic achievement at $t = 0$ may increase the probability of attending post-secondary education, and this particular schooling level has, on average, a positive return on labor market outcomes. Again, our estimates show all these effects on one estimated parameter.

One potential problem with equation (2) is that E_{i,t_0} may not be totally exogenous. As we shall see in section 5 we include school type within this last variable. In this case, wealthier families may prefer to enroll their children in private-fee-paying schools (the proportion of mothers with tertiary education is 40%, 17% and 9% in private-fee-paying, private-voucher and public schools, respectively). Moreover, schools may choose more able students, especially in private-voucher and private-fee-paying schools.¹² If we fail to account for school choice and selection from schools, estimates from the reduced-form model would be biased.

Our identifying assumption consists in including different covariates accounting for family background and proxies for individual's abilities that may be causing this selection bias. We assume that non-observables explaining school choice also predict academic achievement.¹³ In this way, we account for schooling choices in our estimates by including test scores measuring academic achievement. More precisely, let Q_i be a vector of exogenous characteristics, S_i school type and school variables, F_i family background variables, A_i academic achievement as proxies for individual's abilities and P_i public policies that may influence

¹¹Cunha, Heckman, Lochner, and Masterov (2006), Cunha and Heckman (2007) and Cunha and Heckman (2008) provide with a formal analysis about this topic.

¹²Contreras, Sepúlveda, and Bustos (2010) find that the students selection is a common practice among private schools.

¹³Rau, Sánchez, and Urzúa (2011) accounts for unobserved ability using a structural model in a factor structure as in Carneiro, Hansen, and Heckman (2003); Heckman and Navarro (2007). According to their estimates, unobserved ability is a significant factor determining school choice.

school quality. All covariates are measured at a particular period $t_0 < \bar{t}$. We posit the following linear model:

$$w_{i,\bar{t}} = \gamma_1 Q_i + \gamma_2 S_i + \gamma_3 F_i + \gamma_4 A_i + \gamma_5 P_i + v_{i,\bar{t}} \quad (4)$$

Including A_i in this last equation allow us to control for selection bias in S_i . Nonetheless, academic achievement is only a proxy for abilities (that, in turn, is causing selection bias). It is also affected by individual's characteristics, and, again, by school type (Carnoy and McEwan, 2000; McEwan, 2001; Carnoy and McEwan, 2003; Gallego, 2006; Contreras, Sepúlveda, and Bustos, 2010; Elacqua, Contreras, Salazar, and Santos, 2011; Rau, Sánchez, and Urzúa, 2011). Hence, if we include A_i in (4), we are actually absorbing part of the effect of school type in γ_4 . This is a consequence of schools having an indirect effect on earnings through their contribution on raising academic achievement in the short-term. Instead if we omit A_i –in order to get an estimated full impact in a reduced-form equation– we would not account for selection bias arising from school choice and selection from schools and we would overestimate the high school effect on earnings. Therefore, our full-impact unbiased estimated parameter must lie between the estimated γ_2 from a regression including A_i and the corresponding estimate from a model excluding A_i .

5 The Data

We use data coming from the 2001 Measurement System of Education Quality (SIMCE). Every year, the Ministry of Education conduct a national exam to all Chilean students in a particular schooling level. In 2001 The Ministry surveyed 10th graders, which corresponds to students at age 16. These tests measure the individual performance on minimum curricula requirements in different subjects. We use in our analysis math and language test scores.

SIMCE also registers information about students' characteristics and their families. We

define our exogenous characteristics vector (Q_i in equation (4)) by including age, age squared, gender, and previous attendance to pre-primary education. In the family background vector (F_i) we include mother and father’s education, family income and number of books at home. We measure academic achievement (A_i) with language and math test scores and with a variable indicating whether a student has repeated previous schooling levels.

On the other hand, we have data about the two public policies discussed in section 2. We use this information to define two public policy variables. The first one corresponds to a dummy variable taking the unit value if a school has adopted JEC in 2001 and 0 otherwise. The second public policy variable is a vector of dummies where each variable ($SNED_j$) takes the unit value if a school has won SNED j times and 0 otherwise. We have information about 1996, 1998 and 2000 SNED winners.

Finally, SIMCE also contains data on private and public costs on education. In particular, it contains tuition and other related self-reported private expenditures. We also consider public subsidies (vouchers) for public and voucher schools and add them to the private expenditures. Lastly, we include direct transfers from local municipalities to public schools.¹⁴

We observe students’ earnings 10 years from the time they took SIMCE. We extract this data using Unemployment Insurance database. This information records individual’s taxable earnings for formal workers, that is, with formal labor contracts. We have earnings from January to December 2011. Our dependent variable is the average of earnings (including 0’s) over 2011.^{15,16}

SIMCE database accounts for 190,863 students. However, our analysis is based on 76,591 individuals. We obtain this number in three steps. Table 6 shows descriptive statistics on each of these steps. First, we drop students from the database with missing values in some of the covariates included in our regression analysis, which reduces considerably our sample.

¹⁴Source: <http://www.sinim.gov.cl/>. Each district local district reported a total direct transfer to the associated public schools. We then take the average expenditure per-student and include this number into the individual educational investment.

¹⁵However, we exclude from our sample observations having 0’s in all 2011 earnings records.

¹⁶In the Unemployment Insurance data we do not have information on hourly earnings.

As a result, the share of public schools falls, and average earnings and test scores increase. Next, we consider only students affiliated to the Unemployment Insurance System. Being affiliated requires having a formal work contract by December 2011. In this case, average scores are reduced on both language and math scores. This may be a consequence of the fact that ablest students may still be studying by 2011. Consistently, the share of public schools raises at this stage. Finally, leaving observations with 2011 earnings above 0 delivers our final sample.¹⁷ Even though there are some changes in the covariates' averages when going from the initial universe of students to the final sample, the overall representativeness of the former is not seriously compromised in the latter.

In Table 7 we present descriptive statistics for all of the variables that we use in our regression analyses.

6 Results

6.1 The effect of the educational system and academic achievement on the labor market

We now turn to explore into the role of school type on labor market outcomes. Unconditional differences between schools are huge (Table 8, column 1). Attending a private-fee-paying school instead of a public school raises average earnings 34%. Of course, this number accounts not only direct and indirect effects of private schools, but also reflects that better able students, coming from wealthier and more educated families, have a greater probability of attending these schools. If we control for family background and exogenous characteristics, the value-added of private-fee-paying schools reduces to 16.6% relative to public schools. If we add test scores into the equation, the return of private-fee-paying schools over public schools on earnings reduces to 12.5%. On the other hand, attending private-voucher instead

¹⁷This condition is fulfilled for individuals who reported at least one month in 2011 (from January to December).

of public schools at age 16 has a modest impact on subsequent adult wages (about 2.2% to 4.1% depending on the estimate). The difference in academic achievement between private-voucher and public school has been widely analyzed in the literature (Carnoy and McEwan, 2000; McEwan, 2001; Carnoy and McEwan, 2003; Gallego, 2006; Contreras, Sepúlveda, and Bustos, 2010; Elacqua, Contreras, Salazar, and Santos, 2011; Rau, Sánchez, and Urzúa, 2011). Nonetheless, our results represent an additional effect of private-voucher schools on earnings, not fully captured by SIMCE’s differentials. This means that the evaluation of voucher schools on students’ outcomes is incomplete if we do not consider these long-term effects on labor market outcomes.

How we interpret these numbers? Note that academic achievement serves as a proxy for pre-labor market skills. Hence, as we said before, including academic achievement is a simple way of controlling for school choice (column 4 in Table 8). Nonetheless, the estimated coefficient associated with academic achievement would absorb part of the effect of school type through a possible short-term impact on current test scores. Therefore, the full impact of attending private-fee-paying instead of public schools is bounded between 12.5% and 16.6% (column 3 and 4 of Table 8). Analogously, the return of private-voucher versus public schools averages 2.2% to 4.1%.

Early academic achievement has a sizable effect on earnings. The estimated return of math test scores (measured as standardized variables with mean 0 and standard deviation equal to 1) is 14%. The estimates imply that one point of math test scores increases monthly earnings by \$2.3. Causal effects for language test scores are much smaller: 1.6% effect on earnings, which implies a \$0.3 increasing in monthly earnings due to raising one point in the language test score. Remember that our reduced-form models show the full average effect of marginal improvement of academic achievement. It is a reflection that early cognitive improvement increases the likelihood of subsequent increases of abilities in the future (Cunha, Heckman, Lochner, and Masterov, 2006; Cunha and Heckman, 2007, 2008). Furthermore,

more abilities raise the return of attending post-secondary institutions.¹⁸ Finally, a greater stock of abilities may have a direct impact on wages, even after accounting for schooling. This process implies that an early ability gap increases with age. Our estimates accounts for all of these underlying mechanisms in one estimated parameter.

There is also evidence of nonlinear effects of SIMCE score (Figure 5). Indeed, the return on earnings of being in the fifth versus the first quintile of test score is much higher than the return of belonging to the fourth, third or second quintile relative to the first one. The fact that the effect of pre-labor market abilities is increasing with the level of test scores is an element which exacerbates income inequality relative to the initial human capital stock (See Table 4).

Our estimates confirm our conclusions when we discuss the increasing gap between private-fee-paying to voucher and public schools (Figure 4). Attending a private-fee-paying school provides more scope for further increasing in earnings if a student improves his math test scores (column 5 in Table 8). Contrarily, the gap between private-voucher and public schools does not increase with math test scores. Again, these interaction effects explain how initial inequality (at age 16 in this case) is transferred to a further increase in inequality in adulthood.

We also estimate the effect of high achievement schools on future labor market success. We can measure school achievement using the average of SIMCE test score. This also gives us a rough measure of school quality.¹⁹ Our estimates show that high achievement schools have long-term impacts on its students (Table 9). Column 1 in Table 9 implies that an increase of one standard deviation of math's average in a school will increase a student's future earnings by an average of 9%. But high-achieving schools have some interesting heterogeneous impacts. Increasing the average achievement of a school has higher economic benefits for ablest students, as column 2 shows. Nonetheless, this additional effect is relevant only for students attending private-voucher schools (column 3 in the same table). Loosely

¹⁸See Reyes, Rodríguez, and Urzúa (2012).

¹⁹Originally, SIMCE was designed to measure schools' educational quality.

speaking, school overall achievement matters; but if you are a good student, you may want to study in a private-fee-paying school.

6.2 The effect of educational public policies

Using the framework illustrated in equation (4) we estimate the impact on adult earnings of JEC and SNED. Table 13 and 14 present the impact of SNED. Table 13 explores six different models, which are based on the variable $SNED_j$. This variable equals 1 if a school has won j times SNED ($j = 1, 2, 3$). The estimates accounts for individuals' exogenous characteristics, school type, individual academic performance and a dummy variable which equals 1 if a student attends a school having JEC. Our results show a large impact (a rise of 16% in earnings) for schools having won SNED three times. However the positive effect of SNED is revealed only for private-voucher schools (Table 14). Private-voucher schools, winning three times the SNED tournament, generate sizable long-term impacts on student's adult earnings (25%). We must emphasize that these estimates are not the impact of the tournament system itself on earnings, but the long-term effect of good schools, correctly chosen as winners of SNED, on students' labor market outcomes.²⁰ Nevertheless, winning public schools of SNED are not different from the rest of the public schools in terms of their long-term impact on students' earnings.

Table 15 documents JEC impact on earnings. Column 1 shows that the average impact of JEC does not significantly differ from 0. Nonetheless, column 2 presents evidence of the heterogeneous return of JEC. It shows that JEC produces a 5.7% increase in earnings for private-fee-paying schools. Therefore, longer days at school are benefiting only private-fee-paying schools. Hence, the implied public investment associated with JEC increases the income gap between public and private-fee-paying showed in Table 8.

Remember that, because we are including math and language test scores, the same caveat about the returns on types of schools applies in this case. If part of the effect of

²⁰See [Rau and Contreras \(2012\)](#) for a discussion. These authors show a significant effect of SNED on academic achievement measured through SIMCE test score

SNED-winning schools and JEC is transmitted to a higher SIMCE, then our estimates show additional effects of SNED and JEC, not entirely captured by the related improvement in academic achievement.

6.3 The effect of investing in education

In this section we exploit data on private and public costs of education. As mentioned, we have information on tuition and other education-related expenditures from students' families. We obtain total costs by adding to the private expenditures the associated amount of voucher for private-voucher and public schools and direct transfers from municipalities to public schools.

We assume that the cost function of a school includes all school characteristics that help achievement to increase. We also assume that these elements also improve labor market outcomes. Therefore, in order to estimate first-derivatives in the relationship between costs and earnings, we must exclude from our regressions school characteristics and academic performance measures. Let c_i the total investment on education for student i . We estimate the following equation:

$$w_i = \gamma_1 \log(c_i) + \gamma_2 \log(c_i)PV + \gamma_3 \log(c_i)PFP + \gamma_4 Q_i + \gamma_5 F_i \quad (5)$$

where PV indicates studying in private-voucher schools and PFP attending private-fee-paying. Q_i indicates exogenous characteristics and F_i family socioeconomic background.

Private-fee-paying schools have the greatest amount of average investment, followed by private-fee-paying and public schools, which is consistent with the fact that private schools have the highest academic performance, once we account for individual's exogenous characteristics and family background (Table 16). This indicates that higher investment on education implies an increase of academic achievement, a fact that is independent of the

type of school.

Investing in education has a significant and considerable effect on adult earnings, even we control for exogenous characteristics and family socioeconomic background (Table 17).²¹ Our estimate imply that if we want to equalize adult earnings of public and private-fee-paying students we must invest more on students in public schools than on students in private-fee-paying schools. Indeed, equalizing earnings between these two groups would take an increase in the educational investment on public schools students by 1,252%. Meanwhile, the difference in educational investment in these groups is only 52% (Table 16). Moreover, the impact of educational investment in labor market prospects is heterogeneous by school type. Particularly, investing on public schools yields lower returns than the associated gains from investing in private schools.

This evidence confirms the intuition arising throughout our study. Better endowed students (coming from good and private school, with higher pre-labor market abilities) have higher returns of investment in human capital than the disadvantaged ones. Moreover, the cost structure of the educational system, which imply greater educational investment directed to those students in private-fee-paying schools, tends to increase the inherited earnings gap as individuals are passing through the educational system.

7 Conclusions

Our paper explores the origins of income heterogeneity by studying the relationship between early human capital endowments at age 16 and associated adult earnings. We take advantage of a rich data set of administrative records for test scores, individual background, school characteristics and adult earnings. We use simple linear regressions to show the importance of family background, school type and educational public policies directed to improve academic achievement on labor market prospects.

Our results give us new insights about the origins of earnings inequality in Chile, a rapid

²¹We exclude from our sample 455 students from public schools (0.6% of our sample) with $c_i = 0$.

growth country but with high inequality indicators. We already know from the literature that education has been playing a predominant factor, but the specific mechanisms linking education and earnings heterogeneity have not been analyzed in extent.

Several elements reveal the influence of early human capital investment on earnings inequality. We document that different types of school are good predictors of future labor market outcomes of students. Ablest students have more economic benefits from studying in private-fee-paying schools. School overall achievement has an additional impact for good students if these schools are also private-fee-paying. Consistently, if a family invests one dollar of educational resources for students in private-voucher schools, the return of this investment exceeds the associated return on public and private-voucher schools. Finally, the return of pre-labor market skills is increasing with the level of such skills.

On the other hand, two educational policies, directed to improving schools' quality, have long-term effects, but they are not helping to improve earnings inequality.

The elements studied in this paper points to the conclusion that the educational system does not reduce the inherited inequality of individuals as they go through the schooling system. This is a direct consequence of "skills begetting skills". Better endowed students gain more from the schooling system. However, other educational interventions are not helping to compensate for this effect. Our results imply 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.

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Table 1: Educational Policies: SIMCE and Earnings

Policy	Math	Language	Earnings 2011
<i>JEC</i>			
No	242.0	247.1	652.6
Yes	254.1	257.3	703.2
<i>SNED₁</i>			
No	247.4	251.7	675.2
Yes	237.7	242.3	642.8
<i>SNED₂</i>			
No	247.5	251.7	675.3
Yes	234.6	243.3	631.7
<i>SNED₃</i>			
No	247.4	251.6	674.5
Yes	234.9	243.1	700.7

Notes: We show average math and language test scores (SIMCE) and 2011 monthly earnings of students attending schools with JEC or SNED winners. Our data includes information of SNED winners in 1996, 1998 and 2000. $SNED_j$ equals 1 if a student attends a school that won SNED j times ($j = 1, 2, 3$) in the years 1996, 1998 and/or 2000. Earnings information comes from the Unemployment Insurance database. Total number of observations is 72,826 students. This is the same sample of individuals we use in our regressions estimates.

Table 2: Academic performance by school type

School	Language		Math	
	Average	Std. Dev.	Average	Std. Dev.
Public	240.3	46.5	234.5	45.9
Private-voucher	256.4	47.6	250.4	49.1
Private-fee-paying	275.9	49.8	281.3	58.7

Notes: We show the average and standard deviation of SIMCE 2001 test scores for math and language for different types of school. Total number of observations is 72,826 students. This is the same sample of individuals we use in our regressions estimates.

Table 3: Distribution of students by academic achievement and school type

Math test score	Public	Private-voucher	Private-fee-paying	Total
<200	8,429	4,180	745	13,354
200-300	24,917	20,184	6,360	51,461
300-400	3,234	4,569	3,669	11,472
>400	107	117	315	539
Total	36,687	29,050	11,089	76,826

Notes: The table shows the distribution of students by Math test score (SIMCE 2001) and school type.

Table 4: Theil index for income inequality and math test scores (2001) by school type

Group	Theil Earnings	Theil SIMCE Math	Theil SIMCE Language
Public	0.337	0.018	0.019
Private-voucher	0.329	0.019	0.017
Private-fee-paying	0.363	0.022	0.017
Total	0.348	0.021	0.019
Within group	98%	91%	94%
Between group	2%	9%	6%

Notes: The table shows the Theil index of inequality for 2011 earnings and math and language test scores (SIMCE 2001) decomposed by school type. We also present the proportion if within and between school type inequality that explains the total index. Earnings information comes from the Unemployment Insurance database. Total number of observations for the math test score, language test score and 2011 earnings Theil calculations is 72,826 students. This is the same sample of individuals we use in our regressions estimates.

Table 5: Mother's education, SIMCE and earnings

Mother's education	SIMCE Math	SIMCE Language	Monthly 2011 Earnings (US\$)
Primary	230.8	237.0	597.2
Secondary	247.5	252.8	672.5
Vocational Secondary	253.1	258.5	716.6
Two-year postsecondary degree	274.9	273.6	777.1
Four-year postsecondary degree	279.8	278.7	826.1
Five-year postsecondary degree	289.5	284.7	874.4

Notes: The table shows math test scores (SIMCE 2011) and earnings by schooling of student's mothers. Earnings information comes from the Unemployment Insurance database. Total number of observations is 72,826 students. This is the same sample of individuals we use in our regressions estimates.

Table 6: Descriptive statistics by data set

Variables	SIMCE data	Valid obs	Affiliated	Earnings 2011 > 0
Earnings (US\$ 2011)	417.0	421.4	553.8	674.7
Age (2011)	26.2	26.1	26.1	26.2
Language score	251.4	255.6	253.4	251.5
Math score	246.6	251.4	249.1	247.3
Public school (%)	47.6	46.4	47.0	47.8
Private-voucher school (%)	36.6	37.4	37.9	37.8
Private-fee-paying school (%)	15.9	16.2	15.1	14.4
JEC (%)	46.3	45.2	44.4	43.7
SNED_1 (%)	1.4	1.5	1.5	1.5
SNED_2 (%)	1.2	1.3	1.3	1.4
SNED_3 (%)	0.8	0.8	0.8	0.8
Observations	190,863	123,016	93,606	76,826

Notes: This table presents different datasets 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 2001 data. The second column (Valid obs) drops observation with missing values in the SIMCE database in at least one of the variables considered in our regressions. The third column (Affiliated) shows students that are present in the 2001 SIMCE who were affiliated to the unemployment insurance system by 2013. Being affiliated implies having at least one monthly earnings record. Once an individual enters the Unemployment Insurance data it remains in the system even if she never reports a salary again. The fourth column (Earnings 2011>0) presents descriptive statistics for the sample of the previous column that have an average monthly earning of 2011 greater than 0. This is the sample that we use in most of our estimates.

Our data includes information of SNED winners in 1996, 1998 and 2000. $SNED_j$ equals 1 if a student attends a school that won SNED j times ($j = 1, 2, 3$) in the years 1996, 1998 and/or 2000. JEC equals 1 if a student attend to a school that have JEC program and 0 otherwise. Public, Private-voucher and Private-fee-paying are also dummy variables that take the value of 1 if the students attends the respective school type and 0 otherwise.

Table 7: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Average Monthly Earnings (US\$ 2011)	674.7	598.9	0.0	5,423.4
Age (2011)	26.2	2.1	18	75
Language score	251.5	49.0	95.01	410.69
Math score	247.3	51.6	94.67	428.18
Average Monthly Family income (US\$ 2011)	550.7	669.2	200	3800
Public school	47.8%		0	1
Private-voucher school	37.8%		0	1
Private-fee-paying school	14.4%		0	1
Pre-primary (two years)	45.2%		0	1
Pre-primary (one year)	43.9%		0	1
Only primary	10.9%		0	1
Male	54.2%		0	1
Mother's education: primary	41.2%		0	1
Mother's education: secondary	31.2%		0	1
Mother's education: secondary vocational	11.3%		0	1
Mother's education: technical institute (undergraduate)	2.5%		0	1
Mother's education: professional institute (undergraduate)	4.1%		0	1
Mother's education: university (undergraduate)	7.5%		0	1
Mother's education: university (graduate)	2.1%		0	1
Father's education: primary	39.4%		0	1
Father's education: secondary	29.7%		0	1
Father's education: secondary vocational	12.5%		0	1
Father's education: technical institute (undergraduate)	2.9%		0	1
Father's education: professional institute (undergraduate)	3.7%		0	1
Father's education: university (undergraduate)	10.0%		0	1
Father's education: university (graduate)	1.9%		0	1
Books at home (<10)	25.1%		0	1
Books at home (10-50)	43.8%		0	1
Books at home (50-100)	18.2%		0	1
Books at home (>100)	12.8%		0	1
Repeated courses=0	75.3%		0	1
Repeated courses=1	18.2%		0	1
Repeated courses \geq 2	6.5%		0	1
JEC	43.7%		0	1
SNED_1	1.5%		0	1
SNED_2	1.4%		0	1
SNED_3	0.8%		0	1
Observations	76,826			

Notes: Public, Private-voucher and Private-fee-paying are also dummy variables that take the value of 1 if the students attends the respective school type and 0 otherwise. Pre-primary variables are dummy variables that equal to 1 if the student has attended a pre-primary school for the correspondent years (one or two) and 0 otherwise. "Only Primary" equals 1 if the student has not attended a pre-primary institution and 0 else. Mother and Father's educations variables are also dummy variables for each level of education. Books variables indicate the number of books as reported in the 2001 SIMCE. We have information of SNED winners in 1996, 1998 and 2000. $SNED_j$ equals 1 if a student attends a school that won SNED j times ($j = 1, 2, 3$) in the years 1996, 1998 and/or 2000. JEC equals 1 if a student attend to a school that have JEC program and 0 otherwise.

Earnings and Age information comes from the Unemployment Insurance database. The rest of the variables are obtained in the 2001 SIMCE.

Table 8: Earnings regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Private-voucher	0.103*** (0.00953)	0.0474*** (0.0102)	0.0412*** (0.0103)	0.0221** (0.0103)	0.0350*** (0.0104)	0.0222** (0.0103)	0.0202* (0.0103)
Private-fee-paying	0.331*** (0.0134)	0.174*** (0.0161)	0.165*** (0.0162)	0.125*** (0.0162)	0.107*** (0.0164)	0.125*** (0.0162)	0.124*** (0.0162)
Language				0.0153** (0.00650)	0.0178*** (0.00651)	0.0153** (0.00650)	0.0153** (0.00650)
Math				0.140*** (0.00693)	0.119*** (0.00903)	0.140*** (0.00693)	0.140*** (0.00693)
Math*Private-voucher					0.00266 (0.0113)		
Math*Private-fee-paying					0.108*** (0.0148)		
Exogenous characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Family Background	No	No	Yes	Yes	Yes	Yes	Yes
Performance	No	No	No	Yes	Yes	Yes	Yes
Policies (in levels)	No	No	No	No	No	Yes	Yes
Policies (with interactions)	No	No	No	No	No	No	Yes
Obs.	76.826	76.826	76.826	76.826	76.826	76.826	76.826
Adjusted R-squared	0.008	0.038	0.040	0.051	0.052	0.051	0.051

Source: Authors' estimates.

Notes: (i) We show estimates of equation (4). Exogenous characteristics include age (2011), age squared, previous assistant to pre primary education, gender, region and tuition. In family background we include mother and father's education, log of family income and number of books at home. In academic performance variables we include math and language test scores as well as a dummy variable which equals 1 if the student has repeated previous schooling levels. Finally, we include two variables indicating if a student attends a school with JEC or SNED program. (ii) Math and language test scores are defined as standardized variables (with mean 0 and standard deviation 1). (iii) In Column (6) we add dummy variables indicating studying in a school participating in JEC. We also add a dummy variable which equals 1 if a student attends a school winning SNED three times and 0 otherwise. In column (7) we interact JEC and SNED variables with indicators of school type. (iv) Robust standard error are in parenthesis (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Earnings regressions and school average academic achievement

Variables	(1)	(2)	(3)
Private-voucher	0.0181*	0.0228**	0.0403***
	(0.0105)	(0.0106)	(0.0115)
Private-fee-paying	0.114***	0.120***	0.0850***
	(0.0164)	(0.0165)	(0.0169)
Language_i	0.0136**	0.0147**	0.0141**
	(0.00658)	(0.00657)	(0.00657)
Math_i	0.126***	0.121***	0.116***
	(0.00728)	(0.00734)	(0.00750)
Language_j	-0.0419	-0.0235	-0.0255
	(0.0275)	(0.0281)	(0.0281)
Math_j	0.0920***	0.0631**	0.0829***
	(0.0254)	(0.0268)	(0.0268)
Language_i × Language_j		0.00353	0.0140
		(0.0109)	(0.0110)
Math_i × Math_j		0.0209**	-0.0189
		(0.00894)	(0.0132)
Math_i × Math_j × Private-voucher			-0.0284
			(0.0175)
Math_i × Math_j × Private-fee-paying			0.0991***
			(0.0152)
Exogenous characteristics	Yes	Yes	Yes
Family Background	Yes	Yes	Yes
Academic performance	Yes	Yes	Yes
Obs.	76,591	76,591	76,591
Adjusted R-squared	0.052	0.052	0.053

Source: Authors' estimates.

Notes: (i) We show estimates of equation (4). Exogenous characteristics include age (2011), age squared, previous assistant to pre primary education, gender, region and tuition. In family background we include mother and father's education, log of family income and number of books at home. In academic performance variables we include math and language test scores as well as a dummy variable which equals 1 if the student has repeated previous schooling levels. Finally, we include two variables indicating if a student attends a school with JEC or SNED program. (ii) Math and language test scores are defined as standardized variables (with mean 0 and standard deviation 1). Math_j and Language_j are school-level averages of test scores. (iii) Robust standard error are in parenthesis (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 10: For-profit schools and earnings

Funding scheme	(1)	(2)
Private-voucher-nonprofit	0.0999*** (0.0122)	0.0620*** (0.0122)
Private-voucher-for-profit	-0.0310** (0.0130)	-0.0262** (0.0130)
Private-fee-paying	0.159*** (0.0162)	0.122*** (0.0162)
Exogenous characteristics	Yes	Yes
Family Background	Yes	Yes
Academic Performance	No	Yes
Obs.	76.591	76.591
Adjusted R-squared	0.041	0.052

Table 11: Shared-funding schools and earnings

Funding scheme	(1)	(2)
Public-shared-funding	0.0271* (0.0163)	0.0280* (0.0163)
Private-voucher-shared-funding	0.0632*** (0.0117)	0.0394*** (0.0117)
Private-voucher-nonshared-funding	-0.00423 (0.0174)	-0.00763 (0.0173)
Private-fee-paying	0.178*** (0.0167)	0.137*** (0.0167)
Exogenous characteristics	Yes	Yes
Family Background	Yes	Yes
Academic Performance	No	Yes
Obs.	76.591	76.591
Adjusted R-squared	0.041	0.052

Table 12: Shared-funding, for-profit schools and earnings

Funding scheme	(1)	(2)
Public-shared-funding	0.0321** (0.0163)	0.0313* (0.0163)
Private-voucher-shared-funding-for-profit	-0.00913 (0.0144)	-0.00746 (0.0143)
Private-voucher-shared-funding-nonprofit	0.133*** (0.0142)	0.0857*** (0.0143)
Private-voucher-nonshared-funding-for-profit	-0.0864*** (0.0280)	-0.0712** (0.0281)
Private-voucher-nonshared-funding-nonprofit	0.0414** (0.0206)	0.0277 (0.0206)
Private-fee-paying	0.174*** (0.0167)	0.135*** (0.0167)
Exogenous characteristics	Yes	Yes
Family Background	Yes	Yes
Academic Performance	No	Yes
Obs.	76.591	76.591
Adjusted R-squared	0.042	0.052

Table 13: The effect of SNED on earnings

Policy	(1)	(2)	(3)	(4)	(5)	(6)
SNED₁	0.0229 (0.0335)	0.0225 (0.0335)	0.0241 (0.0335)	0.0229 (0.0335)		
SNED₂		-0.0226 (0.0382)	-0.0227 (0.0382)		-0.0231 (0.0382)	
SNED₃			0.159*** (0.0466)			0.158*** (0.0466)
Exogenous characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Family Background	Yes	Yes	Yes	Yes	Yes	Yes
Academic performance	Yes	Yes	Yes	Yes	Yes	Yes
School type	Yes	Yes	Yes	Yes	Yes	Yes
JEC	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	76,591	76,591	76,591	76,591	76,591	76,591
Adjusted R-squared	0.052	0.052	0.052	0.052	0.052	0.052

Source: Authors' estimates.

Notes: (i) We show estimates of equation (4). Exogenous characteristics include age (2011), age squared, previous assistant to pre primary education, gender, region and tuition. In family background we include mother and father's education, log of family income and number of books at home. In academic performance variables we include math and language test scores as well as a dummy variable which equals 1 if the student has repeated previous schooling levels. Finally, we include school type (private-voucher or private-fee-paying). (ii) Math and language test scores are defined as standardized variables (with mean 0 and standard deviation 1). (iii) We add a dummy variable which equals 1 if a student attends a school with JEC, 0 otherwise. (iv) $SNED_j$ equals 1 if a student attends a school winning SNED j times ($j = 1, 2, 3$). (v) Robust standard error are in parenthesis (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 14: The effect of SNED on earnings by school type

Policy	(1)	(2)	(3)
Public*SNED₁	0.0457 (0.0426)		
Private-voucher*SNED₁	-0.00553 (0.0535)		
Public*SNED₂		-0.0241 (0.0417)	
Private-voucher*SNED₂		-0.0176 (0.0953)	
Public*SNED₃			0.0855 (0.0662)
Private-voucher*SNED₃			0.253*** (0.0635)
Exogenous characteristics	Yes	Yes	Yes
Family Background	Yes	Yes	Yes
Academic performance	Yes	Yes	Yes
School type	Yes	Yes	Yes
JEC	Yes	Yes	Yes
Obs.	76,591	76,591	76,591
Adjusted R-squared	0.052	0.052	0.052

Source: Authors' estimates.

Notes: (i) We show estimates of equation (4). Exogenous characteristics include age (2011), age squared, previous assistant to pre primary education, gender, region and tuition. In family background we include mother and father's education, log of family income and number of books at home. In academic performance variables we include math and language test scores as well as a dummy variable which equals 1 if the student has repeated previous schooling levels. Finally, we include school type (private-voucher or private-fee-paying). (ii) Math and language test scores are defined as standardized variables (with mean 0 and standard deviation 1). (iii) We add a dummy variable which equals 1 if a student attends a school with JEC, 0 otherwise. (iv) $SNED_j$ equals 1 if a student attends a SNED-winner school j times ($j = 1, 2, 3$). (v) Robust standard error are in parenthesis (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 15: The effect of JEC on earnings

Policy	(1)	(2)
JEC	-0.00455 (0.00905)	
Public*JEC		-0.0220* (0.0130)
Private-voucher*JEC		-0.00315 (0.0144)
Private-fee-paying*JEC		0.0569** (0.0263)
Exogenous characteristics	Yes	Yes
Family Background	Yes	Yes
Academic performance	Yes	Yes
School type	Yes	Yes
SNED	Yes	Yes
Obs.	76,591	76,591
Adjusted R-squared	0.052	0.052

Source: Authors' estimates.

Notes: (i) We show estimates of equation (4). *JEC* equals 1 if a student attends a school with JEC, 0 otherwise. Exogenous characteristics include age (2011), age squared, previous assistant to pre primary education, gender, region and tuition. In family background we include mother and father's education, log of family income and number of books at home. In academic performance variables we include math and language test scores as well as a dummy variable which equals 1 if the student has repeated previous schooling levels. Finally, we include school type (private-voucher or private-fee-paying). (ii) Math and language test scores are defined as standardized variables (with mean 0 and standard deviation 1). (iii) We add a dummy variable which equals 1 if a student attends a school winning SNED three times and 0 otherwise. (iv) Robust standard error are in parenthesis (** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 16: Total average cost (private and public) of education by school type and academic performance

Math test score	Public	Private-voucher	Private-fee-paying	Total
< 200	83.6	94.1	59.4	85.5
200 – 300	80.4	99.0	100.8	90.2
300 – 400	86.1	107.2	207.2	133.1
> 400	95.5	116.8	247.0	188.6
Total	81.7	99.7	137.3	96.5

Source: Authors' estimates.

Notes: We show average costs of education. We calculate them as the sum of the monthly tuition cost paid by families and other self-reported expenses. We add to this last number the amount of subsidy associated for private-voucher and public schools and direct transfers from municipalities to public schools. We also consider additional subsidies for schools with JEC.

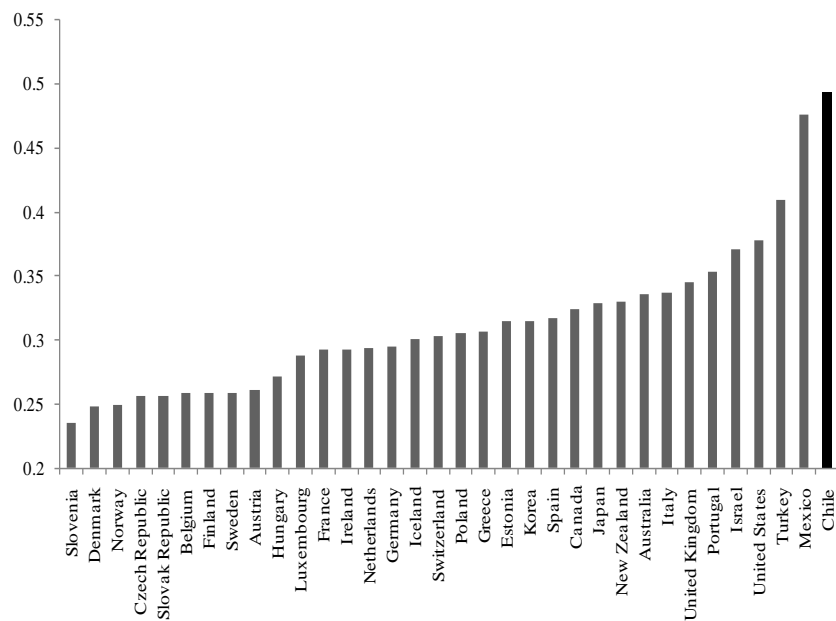
Table 17: Total cost (private and public) of education by school type

Variable	Estimate
Log(cost)	0.027*** (0.009)
Log(cost)*Private-voucher	0.014*** (0.002)
Log(cost)*Private-fee-paying	0.066*** (0.004)
Exogenous characteristics	Yes
Family Background	Yes
Type of school	$\partial \log(w_i)/\partial \log(Cost)$
Public	0.027
Private-voucher	0.040
Private-fee-paying	0.093

Source: Authors' estimates.

Notes: We show estimates from equation (5). The average cost is calculated as the sum of the monthly tuition cost paid by families and other self-reported expenses. We add to this last number the amount of subsidy associated for private-voucher and public schools. We also consider additional subsidies for schools with JEC.

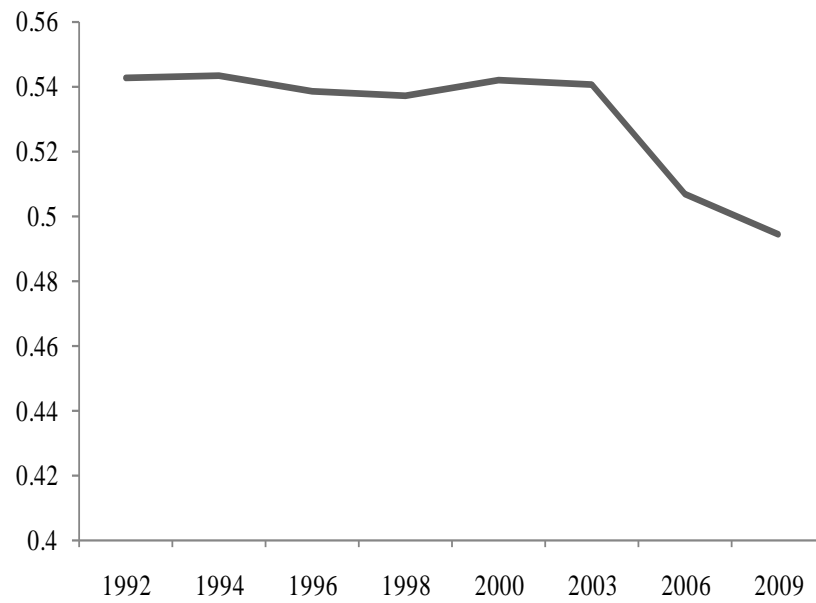
Figure 1: Gini Coefficient for OECD countries (late 2000)



Source: OECD

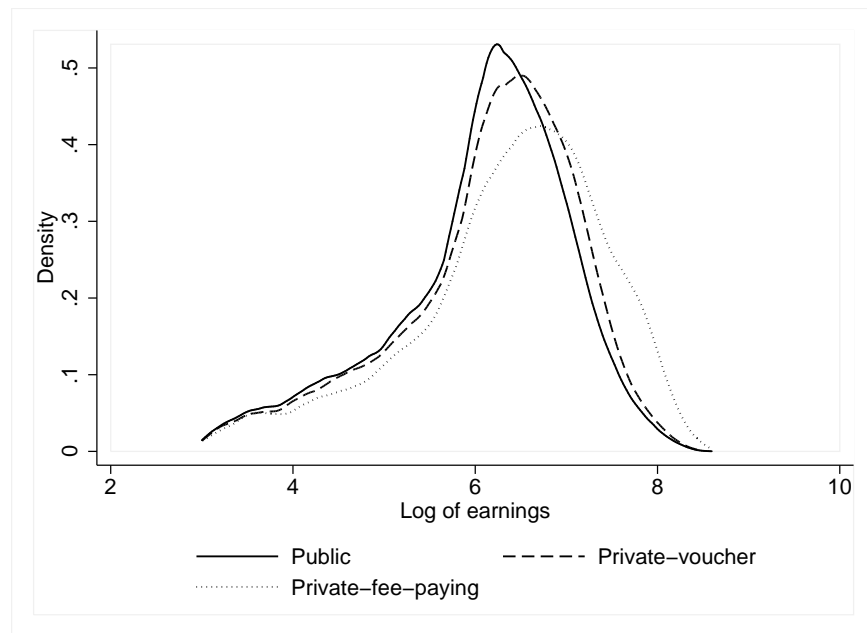
Note: We show Gini coefficients for household income, before taxes and transfers. Not all indicators are from the same year, although, all of them are computed based on late 2000 data.

Figure 2: Gini evolution for Chile



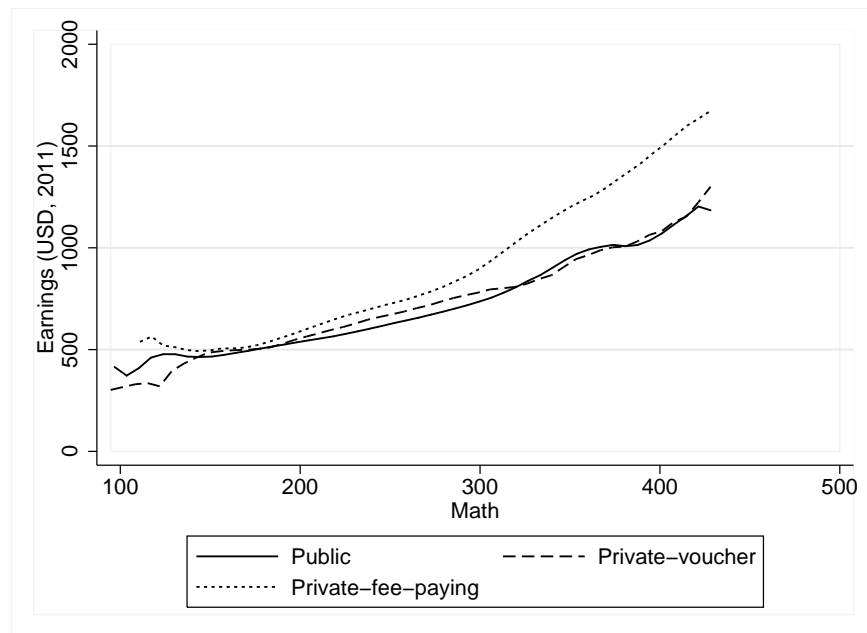
Source: Author's estimates based on CASEN.
Notes: We show Gini coefficient for individual's wages in

Figure 3: Wage distribution and school type



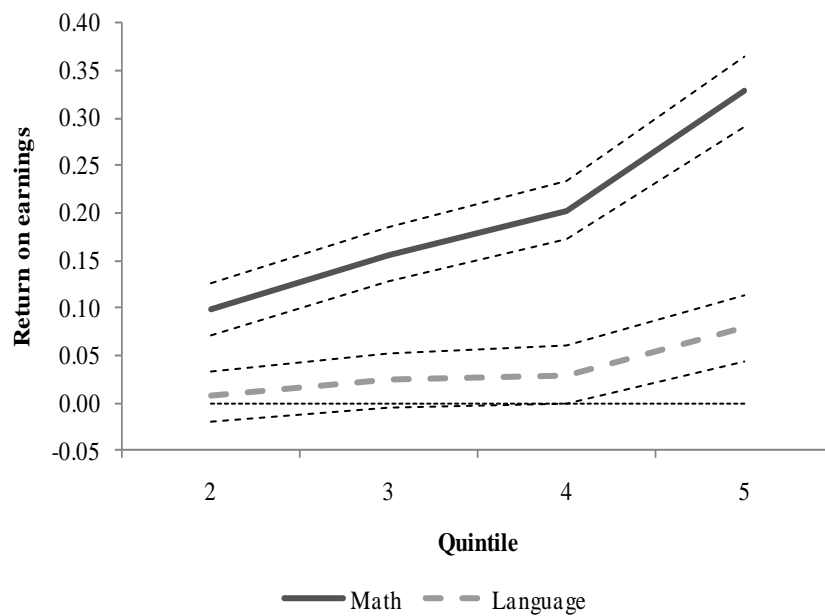
Source: Author's estimates.

Figure 4: Earnings (2011) and SIMCE test scores



Source: Author's estimates.

Figure 5: Labor market return of academic achievement



Source: Author's estimates.

Notes: We show estimates of equation (4), including dummy variables for having a test score (math or language) belonging to the $j = 2, 3, 4, 5$ quintile. We include exogenous characteristics such as age (2011), age squared, previous assistant to pre primary education, gender and region. We also control for include mother and father's education, log of family income and number of books at home, math and language test scores as well as previous repeated courses. Finally, we include school type (private-voucher or private-fee-paying).