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“The Soft Part of Wages: Longitudinal Data Evidence for Chile”

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Abstract: Using a longitudinal database that follows 100,899 individuals through nine years of their life from high school into labor market, we are able to identify cognitive and non-cognitive abilities at school age and their effect on wages. For measuring the effect of soft skills on wages we use two proxies: average school attendance and school grades ranking.

Since an individual's productivity is compound of both abilities both types of skills may impact outcomes such as test scores, dropout rates, and wages. While the effect of cognitive skills is widely studied, yet little has been said about the role of soft skills on such outcomes in less developed countries.

Our main finding is that non-cognitive abilities are as or more important as cognitive abilities in explaining wages. One standard deviation increase in math SIMCE score raises wages by 2.36% while the same change in grades ranking increases wages by 5.03%.

These findings are particularly important in a context of a high inequality country like Chile. The fact that trainable non-cognitive abilities affect wages is another opportunity for social policy to reduce the existent wage gaps in a cost effective way.

Keywords: Education, Inequality, Non-cognitive, Abilities, Wages, Dependence, Test scores.

JEL CODES: I24, I26, J24

Introduction

The estimation of schooling returns has been a topic of interest for economists since the model developed by Mincer (1974). Using Mincer's equation it has been possible to estimate returns to quantity and quality of education[1], the impact of labor experience in wages[2] and many others variables. Most works conclude that the accumulation of human capital makes individuals more productive, which is prized in the labor market with higher wages.

In this context, the individual's skills are an important line of research since they directly impact human capital accumulation. The literature on human capital accumulation has shown that it is easier for the most skilled individuals to educate and train themselves and therefore they would have both better academic performance and better results in the labor market.[3] There is evidence that genetics play a major role in explaining the origins of the differences in human cognitive ability[4]. This would determine differences in the performance of adults in the labor market and would limit the effectiveness of public policies towards disadvantaged populations. There is also evidence that cognitive abilities are malleable only through the first years of the life cycle and are costly to train.

Recent evidence establishes the power of other types of abilities, non-cognitive ones, and an important role for the environment and interventions in creating such abilities.[5] There is evidence that this type of skills might be shaped through all of an individual's life in a cost effective way. In other words, we can say that a part of each individual's productivity is genetically defined, but there is an important role for interventions, education, interaction with others, and work experience among other life experiences in the development of non-cognitive abilities.

The purpose of our paper is to analyze the effect of non-cognitive skills on wages and their magnitude in relation to cognitive skills and other educational variables in Chile. Productivity is created by both cognitive and non-cognitive abilities and so improving both types of abilities might have a positive and direct impact in the development and the potential productivity of an individual, and an indirect impact on his wage.[6]

[1]See Psacharopoulus (1981); Card & Krueger (1992).
[2]See Mincer & Polachek (1974).
[3]See Cunha et. al (2007).
[4]See Herrnstein & Murray (1994).
[5]See Cunha, Heckman, Lochner & Masterov (2006).
[6]Duncan & Dunifon (1998); Heckman, Hsse & Rubinstein (2000); Bowles & Gintis (2001)

The effect of cognitive abilities has been extensively studied; numerous studies establish that measured cognitive abilities are a strong predictor of schooling attainment, wages and social behaviors.[7] However, despite that many authors in developed countries have demonstrated that perseverance, discipline, personality traits, and motivation are important in explaining wage trajectories and success in life, there has little been said about the real effect of non-cognitive variables on wages in the less developed countries (LDCs) because of the lack of quality data that allows us to measure these effects in a reliable way.

The fact that the effect of cognitive abilities on wages is widely studied and that the study of non-cognitive abilities remains under developed is explained by the availability of data sets and the ease of measuring cognitive abilities with standardized test scores. There exist many national and international exams in each subject that can be used to measure the effects of cognitive abilities on different outputs such as wages, high school dropout rates, repetition rates, among others. While, non-cognitive abilities are much difficult to quantify and to study and so we have to use imperfect proxies of persistence, motivation, responsibility, and self-control.

This ease to measure cognitive skills has resulted in the fact that tests scores (as proxies for cognitive abilities) play an important role in sorting and selecting people according to their results. Nonetheless, there is evidence that scores predict only a small fraction of the variance in later life success[8] and they do not adequately capture non-cognitive skills.[9] In order to consider the fact that non-cognitive abilities could be as useful to screen as cognitive abilities[10], Google stopped asking for test scores and academic records. Instead, they make a rigorous selection process consistent of individual and group interviews, where the applicants are asked to imagine themselves in different positions and to illustrate situations of their lives.[11]

Chile is a developing country with high levels of inequality. This inequality also exists in the educational system. According to Valenzuela & Bellei (2008), Chile's formal education is highly economically segregated, both in primary and secondary education and on economic basis. The most vulnerable students mostly attend (70%) municipal establishments[12] while children of high socioeconomic status mainly attend private fee-paying schools that account for about 7% of Chilean

[7]Cawley, Conneely, Heckman & Vytlacil (1997)
[8]Heckman & Kautz (2012).
[9]Heckman & Kautz (2014).
[10]Cawley, Heckman & Vytlacil (2001),
[11]As said by Lazlo Bock, Google Human Resources Vice president, in an interview with "The New York Times"
[12]Elaqua & Pacheco (2005)

schools.[13] Many studies agree on the level of segregation observed in the Chilean educational system although the results differ depending on the methodology used. Chile is considered by the literature as a country with a medium-high level of educational segregation even within Latin American countries.[14]

But Chilean education it is not only economically segregated: it is also quality segregated. According PISA 2012 test scores that ranked Chile in the 51th place among 65 countries, 52% of students don't have a minimum base to face math challenges. Chilean results are far below the OECD average. Furthermore, the findings of Mc Ewan (2001), Elacqua (2005) and others that public and voucher schools perform seemingly in test scores, together with the fact that private schools average test scores higher than the OECD average give us evidence to say that the quality of the education provided both in public and public voucher schools is poor, while private schools quality is acceptable within OECD standards.

Nowadays, cognitive skills are commonly trained in formal education so those with better educational opportunities could acquire great advantages on cognitive skills. However, there are many opportunities to build non-cognitive skills outside of the educational system, which could greatly help the more disadvantaged.

Since initially both skills are evenly distributed among the population[15] finding that soft skills are important to explain wages gives an space for public policy in reducing inequality: training and improving non-cognitive abilities could become an equalizing wage factor. Investments in improving soft skills could have high returns through all the life cycle of a particular individual because of the continued malleability of the pre-frontal cortex that is related to emotions and self-control.[16] Besides, studies suggest that late stage programs to improve socio-emotional skills are more effective among students who are still enrolled in secondary schools.[17]

By contrast, investments in cognitive abilities have to be made in early childhood in order to be cost effective. According to Heckman (2012) that is the only way to consider the fact that skills beget skills. There is also evidence that IQ levels remains stable after the age of 10.[18] Furthermore, investments in cognitive abilities take long time and are costly to make; non-cognitive skills are an

[13]Garcia-Huidobro & Bellei, (2003); Elaqua, (2007)
[14]Valenzuela, Bellei & de los Ríos (2014), Bellei (2013), Arzola & Troncoso (2013), Alves et al. (2015).
[15]Contreras and Gonzalez (2015),
[16]Fuster (2002), Fuster(2013) and Sigman et al (2014).
[17]Heckman and Kautz, (2012); Cunha et al;.(2010)
[18]Koelsch (2012) and Almund et al. (2011)

opportunity to compensate for the low quality education provided in almost 93% of Chilean public and public voucher schools.

Heckman, Stixrud and Urzua (2006) found that in United States non-cognitive skills are as important as cognitive skills in explaining a variety of labor market and behavioral outcomes. With these results, the authors explain the fact that there are students with high scores on standardized tests who perform poorly in the labor market can be explained by deficiencies in non-cognitive skills.

Our identification strategy consists of setting up reduced form equations to account for the role of cognitive and non-cognitive abilities of the individual on wages heterogeneity. Contreras, Rodríguez & Urzúa (2015) used a longitudinal database to observe the individuals path from SIMCE[19]to labor wages and conclude that high school type is an important source of earnings inequality and that human capital investments have larger returns for students in private schools, even after controlling for selection. Following Contreras et al. (2015) and adding non-cognitive variables to their estimations, we are able to examine their importance and to verify if earnings inequality among high school types remains when controlling for such variables.

Our longitudinal database allows us to reveal the linkages between education and adult wage heterogeneity controlling for unobservables that could bias the estimation of causal effects. By controlling for a wide set of family background variables, primary, secondary and tertiary education, and labor market decisions, we can clean up the effects of our variables on the main outcome.

Our approach follows closely the literature that emphasizes the importance of early educational investments. However, our main contribution to this line of analysis is to quantify the effect of non-cognitive skills on future wages and compare it with the impact of the traditional determinants of wage differentials. While these types of studies have already been conducted in developed countries, estimating the importance of non-cognitive skills in a less developed country with high levels of inequality has not been done and becomes very relevant because it can contribute concrete evidence to the planning of public policies to promote greater social mobility.

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[19]The SIMCE (System Measurement of Quality of Education, for its acronym in Spanish), is the system used by the Ministry of Education of Chile to evaluate the country's education system. Through a measurement applied to all students in the country enrolled in the levels evaluated, it seeks to assess the learning outcomes of establishments, evaluating the achievement of the curriculum content and skills existing in different subjects or areas of learning.
The subjects currently evaluated by SIMCE are: Language and Communication (Reading Comprehension and Writing); Math; Natural Sciences; History, Geography and Social Sciences; and English.
For more information about this system, visit www.simce.cl.

The development of non-cognitive skills and their impact on different outputs has been an important subject of study for psychology, a field where they have developed multiple theories. One of these areas of study is related to the influence of personality in human life, a field of research that has for years struggled with the question of what are the most important personality traits.

“The Big Five” is a theory of psychology that investigates the impact of different personalities on an individual’s mental state, affective experience, and behavioral expression. The Big Five defines five relatively distinct domains of important individual differences: openness to new experiences, conscientiousness, extraversion, agreeableness, and neuroticism.[20]

For purposes of our study, we focus our attention on conscientiousness. This concept is related with the tendency to being organized and dependable, showing self-discipline, acting dutifully, aiming for achievement, and preferring planned rather than spontaneous behavior. These characteristics are directly related with the proxies that we will use in our article: school attendance and a ranking of school grades.

Many authors have studied the personality trait of conscientiousness and in general they found that individuals with this characteristic are more motivated to learn, are more likely to set goals and are more likely to be committed to goals. They also perform better at their jobs.[21]

To meet the lack of data on non-cognitive variables we seek to measure the effort, motivation, persistence, responsibility and desire for self-improvement by using the average school attendance at secondary school and a general grade ranking by educational establishment.

Because of our data availability, we calculate the average school attendance over the last three years of secondary school. With this measure we try to reflect the degree to which students during their final school years showed responsibility, motivation, and effort in their schooling. Our hypothesis is that students who have exceptional attendance are individuals who have this type of non-cognitive skills, which are certainly fundamental for personal development and to achieving objectives, which is supposed to be reflected in labor market.

Then grade ranking is a mixture of both cognitive and non-cognitive skills. The relative position between students in their grades within their establishment may reflect motivation, effort, persistence, and desire for self-improvement. Moreover, the grade average reflects the effort throughout the year, and includes different disciplines such as music, art, and physical education that require non-cognitive skills. We are assuming that students with better position relative to their

[20] For a greater understanding of The Big Five see Pervin & John (1999) and John & Srivastava (1999).
[21] See Hogan & Ones (1997), Barrick, Mount & Strauss (1993) and Colquitt & Simmering (1998).

peers, as well as having better cognitive skills, have better non-cognitive skills, which will be rewarded in the future in the labor market.

Brent W. Roberts, leading personality psychologist, suggests that all psychological measurements are calibrated on measured behavior or tasks broadly defined such as school attendance and school performance. Following this idea, some authors have used school attendance as an output to measure the impact of non-cognitive abilities. For example, Holmlund and Silva (2014) sought to assess the impact of an educational program aimed at improving non-cognitive skills such as self-confidence, locus of self-esteem, and motivation with the aim of improving, among others, school attendance.

West et al (2014) found that at the student level, scales measuring conscientiousness, self-control, grit, and growth mindset are positively correlated with attendance; so, measures of non-cognitive skills are positively correlated with student attendance. Jackson (2012) found that both grades and attendance were highly correlated with school performance, that they were unrelated to each other, and that attendance had a high correlation with other behavioral measures. Ramos et al.(2013) found that high school ranking in graduation class raises the individuals salary 10 years later by the equivalent of one year of additional experience, suggesting that ranking stands for a more permanent non-cognitive skill such as effort or self-discipline.

As previously mentioned, the aim of this paper is to add evidence to the extensive literature on personality and non-cognitive skills by studying the case of a less developed country with high levels of inequality and a poor educational system and where developing soft skills may be much more relevant. The paper is structured as it follows: after this introduction, we introduce the Chilean educational system. In Section 3 we briefly present the model on which our identification strategy is based. Then we validate our non-cognitive measures. Section 5 presents the database and its descriptive statistics. Section 6 shows and discuss the results. Section 7 makes a robustness analysis of the ranking measure and finally Section 8 concludes.

Validation of our Non-Cognitive Measures

As said in the introductory section, many authors have used both ranking and attendance as non-cognitive abilities proxies. Nonetheless, it becomes necessary to demonstrate it with data, and in order to convince the reader that the ranking and average attendance are Non-Cognitive measures, in this section we are going to conduct a few analyses relating known non-cognitive measures in other databases with our own proxies.

As said before, one of the problems of the estimation of the effect of non-cognitive abilities is the lack of data and the need to use proxies, and this is not the exception. In the 2014 edition of the SIMCE some non-cognitive-related questions where included. There were three types of questions: The first group of questions where ¿How much do you agree with each of the following statements? And are related with responsibility. Some of the statements where "If I have a bad grade I study harder for the next test" "If I miss classes I get the material to catch up". The second group of questions are related to motivation and expectations, and one of the questions is "When I am an adult I will achieve everything that I propose". In both types of questions, we assigned value 1 to those who answered with a high level of agreement and 0 otherwise. The third type of questions are related to respect and adequacy to situations. The questions are "How bad do you think it is…" and some of them are related to copying, stealing, etc. In this case we assigned value 1 to those who thought the "Really bad" option and 0 otherwise.

Each of the questions were regressed with our Non-Cognitive measures. Then we grouped them constructing three averages indicators and regress the indicators with the grades ranking and average attendance of that database. The results can be seen in table 1, where can be seen that both ranking and attendance are statistically significant and positive in column 1 and 3. Attendance loses it statistical significance in column 2. From table 1 we can infer that ranking and attendance are measuring non-cognitive abilities.

Table 1: Validation of Non-Cognitive Measures

VARIABLES	(1) Responsibility Indicator	(2) Motivation Indicator	(3) Adecuacy Indicator
Grades Ranking	0.0594***	0.00607***	0.0104***
	(0.00120)	(0.000880)	(0.00180)
Attendance	0.00254***	1.60e-05	0.000619**
	(0.000170)	(0.000122)	(0.000249)
Math Simce	3.92e-05*	0.000293***	7.18e-05**
	(2.19e-05)	(1.56e-05)	(3.20e-05)
Language Simce	1.51e-05	0.000206***	0.000188***
	(2.74e-05)	(1.96e-05)	(4.00e-05)
Motivation Indicator	0.209***		0.0620***
	(0.00626)		(0.00924)
Adequacy Indicator	0.151***	0.0148***	
	(0.00302)	(0.00221)	
Responsibility Indicator		0.107***	0.322***
		(0.00319)	(0.00644)
Constant	0.250***	0.730***	0.315***
	(0.0171)	(0.0118)	(0.0249)
Observations	48,892	48,892	48,892
R-squared	0.172	0.086	0.071

The Chilean Educational System

The Chilean educational system is divided into three levels: primary, secondary, and tertiary. The first two levels have three kinds of administration: public, private voucher, and private establishments. Public schools are funded by a state subsidy (student subsidy) and are under municipal administration, while private-voucher establishment are funded by the student subsidy and administrated by the private sector. Finally, private fee-paying establishments are funded and administrated by the private sector. The difference in the funding program between the public and private-voucher schools is that the private subsidized schools can charge tuition to parents and they can select their students unlike charter schools in other countries.

Public schools cannot select their students unless the demand overcomes spaces while private schools are free to select their students based on their own criteria.

Primary education is mandatory and consists of eight years of schooling usually between 7 and 14 years-old. Secondary education, also mandatory, covers four or five years and can be either technical or humanistic. Students are usually 15 and 19 years-old. Technical schools are generally designed for students who want to get a technical diploma and then enter the labor market at an early age.

Throughout this process of primary and secondary education, students across the country take the SIMCE test (System for Measuring the Quality of Education) in 2nd, 4th, 6th, 10th and 11th grade. This test is given by the Education Quality Agency and its goal is to provide relevant information for the different actors of the educational system to help them improve the quality and equity of education. They report on learning achievements of students in different subjects of the national curriculum, and relating them to the school and social context of students.

The Model

Our model — based on Heckman, Vytlacil & Cawley (1998) — seeks to control for relevant variables and decisions that could impact the future salary of each individual and which certainly build the individual's labor productivity over time. Thus, observing our interest variables, e.g. our different ways of representing non-cognitive abilities, we can analyze if such abilities are important and in which measure they explain future salaries.

We regress an OLS model with robust standard errors for Longitudinal data. Applying the model to our data, our main estimation is as follows:

$$W_{i,\tilde{t}} = \alpha + \beta_1 NC_{it-k} + \beta_2 C_{it-j} + \beta_3 Q_i + \beta_4 F_i + \beta_5 S_i + \beta_6 L_i + V_{i,\tilde{t}} \qquad (1)$$

Unlike previous studies of discrimination in the labor market in Chile, in our paper we use Longitudinal data and no cross-sectional data. Our identification strategy consists in setting up reduced form equations to account for the role of cognitive and non-cognitive abilities of the individual on wage heterogeneity. Our Longitudinal database allows us to reveal the links between education and adult wage heterogeneity controlling for unobservables that could bias the estimation of causal effects. We do so by eliminating fixed effects in time to control for non-observables that might be affecting wages. This way, the effect of non-cognitive abilities can be measured in a reliable way; by controlling for a wide set of family background, primary, secondary and tertiary education variables, and labor market decisions, we can clean up their effects on our main outcome. This gives us sufficient confidence that we are correctly defining the productivity of individuals so when analyzing differences in wages caused by our non-cognitive measures, we can claim they are causal effects.

We want to explain the wages earned by individual "i" – measured by its logarithm – at the time t (2012). NC_i stands for non-cognitive abilities. We use mean assistance between 2003 and 2006 and grade rankings in 2003 as proxies. These outcomes are measured at t-9 (2003) and t-6 (2006) respectively. C_i stands for cognitive abilities where we use Math and Language SIMCE scores as proxies. Q_i corresponds to individual characteristics such as age, age squared, gender and if her residential area is urban or rural. F_i are familiar characteristics such as parental education, number of books at home, parental expectations about the level of education their child would reach and family income. S_i is a vector of education characteristics, which include variables such as school type, tertiary education type, area of study, years of education and three dummies that indicate if the individual did or did not: (i) attend pre-primary education, (ii) finished school and (iii) finished his tertiary studies. L_i represents work area of the individual, effective experience and its square. Finally, v_{it} is an error term.

The interest variables from specification 1 are NC_i and its weight against C_i and other characteristics: We want to see if non-cognitive abilities are important in explaining wages and to what magnitude.

The Data

We use a longitudinal database that follows individuals who take math and language SIMCE in 2003 when they were studying their second year in high school at age 15-16 and who declare to be working at 2012 when they are 24 years old, so we can therefore obtain their average monthly wage on annual bases from the Unemployment Insurance database. In Chile, most 24 years old individuals are expected to be working after finishing their tertiary studies.

The advantage of this longitudinal database has to do with the fact that from the SIMCE questionnaire we can obtain important information about family background, educational characteristics, and school attainment, which are essential information in explaining labor market performance and differences in future wages.

Table 2 presents key variable averages as we clean and merge the SIMCE and Unemployment Insurance databases. In any case that an observation had no available data on the secondary controls, we impute them a coherent average with its school type, income level and parental education. This was made in order to maintain the number of observations and their averages.

The first column of Table 2 shows the original sample of the 2003 SIMCE that contains 237.306 observations. In the second column we present the SIMCE data after we drop invalid observations such as individuals with missing values or misreporting ages (eg: individuals of 6 years old in high school). This main data was complemented with RECH-SIGE data (Chilean students register and general student information system) observations from 2003 to 2010, which allows us to distinguish the gender of each individual and their school type among others. The third column shows the descriptive statistics for 156,693 individuals as we merge the valid SIMCE observations with the Unemployment Insurance database. Here we consider affiliated individuals (i.e. having at least one monthly earning record). In the following column (Earnings 2012) we drop observations with average monthly wages under 20 dollars in 2012, for being considered too low. Finally, in the last column we present the descriptive statistics of our final sample, which it is composed of all individuals who meet the above filters and that have available the necessary variables to build our proxies of non-cognitive skills. Our sample allows us to make our estimates for 100,899 individuals for almost 10 years.

Table 2: Descriptive Statistics by Data Set

	Simce Data	Valid Obs.	Affiliated	Earnings 2012	Non Cognitive Ability
Earnings 12'	$448	$456	$555	$772	$782
Age	24.89	24.88	24.90	24.91	24.84
Simce Mat	247.83	247.85	242.55	240.44	243.96
Simce Leng	254.26	254.28	250.22	247.84	250.73
Public School	0.48	0.47	0.48	0.49	0.48
P. Voucher	0.40	0.40	0.41	0.40	0.41
Private	0.12	0.13	0.11	0.11	0.11
Observations	237,306	190,525	156,693	112,645	100,899

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 2003 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 2012. 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 2012) presents descriptive statistics for the sample of the previous column that reported coherent average monthly earning in 2012. Our last column shows the descriptive statistics of the individuals for whom data is available to build our proxies of non-cognitive abilities (attendance and ranking of grades). To convert from Chilean peso to dollar we use the average exchange rate for 2012: $486,49 pesos/dollar

As we expected, there is a bias in our estimations due to the fact that we consider only the individuals that by 2012 had reported wages. This problem arises because workers who report their wages are formal workers, and only 72.8% of workers are formal workers according to CASEN 2011. This would bias our results upward because formal workers tend to earn higher wages than informal workers. According to CASEN 2011 data, informal workers earn about 48.2% of what formal workers earn. Another bias source is the fact that by 2012 there could be still many high skilled individuals who are still in school instead of working in the formal labor market because of failing or because they are studying longer careers or specializing.

Also, it is necessary to consider that when estimating the effect of non-cognitive abilities on wages, it could be underestimated due to the fact that the estimation includes variables related to this type of ability. In effect,we expect soft skills to have an indirect effect on wages through variables such as finishing secondary or tertiary studies.

The interest variables of our estimates are the proxies we constructed to represent persistence, responsibility, effort, and motivation. The first proxy is the average school attendance between 2003 and 2006 (the last years of secondary education). This average is shown as a percentage, where 100% represents full school attendance during those years.

Our second proxy is a ranking of the general average grades for each school in 2003.This average grades includes the performance in all the disciplines included in the mandatory curriculum such as math, language, history, science, physical education, and art. It was standardized by school in order to control for its size and it is ordered from the worst to the best grade (i.e, the worst student in the school is the first student in the ranking).

At the student level, scales measuring conscientiousness, self-control, grit, and growth mindset are positively correlated with attendance, so, measures of non-cognitive skills are positively correlated with student attendance.[22] In addition to school attendance, Jackson (2012) used grades as a proxy of non-cognitive skills. He found that both grades and attendance were highly correlated with school performance, that they were unrelated to each other, and that attendance had a high correlation with other behavioral measures.

Table 3 shows the summary statistics for all the variables in our estimations:

[22]West et al. 2014

Table 3: Summary Statistics

Variable	Mean	Std. Dev.
Cognitive Abilities Proxies		
Math score	243.96	56.1
Language score	250.73	47.5
Non-Cognitive Abilities Proxies		
Average school attendance (2003-2006)	91.9	8.48
Standardized Grades Ranking (2003)	.063	0.98
Individual Characteristics		
Average Monthly Income (2012)	$782	$539
Men	0.54	0.5
Age	24.8	0.7
Urban area	0.83	0.38
Years of Schooling	5.06	1.91
Effective Labor Experience in months	38.8	23.29
Finish Secondary Education	0.95	0.23
Finish tertiary Education	0.14	0.35
Educational Characteristics		
Public	0.48	0.5
Private-Voucher	0.41	0.49
Private-fee-paying	0.11	0.32
Average school grades (2003)	5.4	0.57
Family Characteristics		
Family Income (w<$434)	0.781	0.413
Family Income ($434<w<$868)	0.142	0.349
Family Income ($868<w<$1,446)	0.04	0.196
Family Income ($1,446<w<$2,025)	0.013	0.115
Family Income ($2,025<w<$2,603)	0.007	0.084
Family Income ($2,603<w)	0.016	0.126
Mother`s Ed.: primary	0.371	0.483
Mother`s Ed.: secondary	0.362	0.481
Mother`s Ed.: secondary vocational	0.129	0.335
Mother`s Ed.: technical institute (undergrad.)	0.027	0.162
Mother`s Ed.: professional institute (grad.)	0.038	0.192
Mother`s Ed.: university (undergrad.)	0.05	0.218
Mother`s Ed.: university (grad.)	0.005	0.071
Father`s Ed.: primary	0.326	0.469

Father`s Ed.: secondary	0.372	0.483
Father`s Ed.: secondary vocational	0.141	0.348
Father`s Ed.: technical institute (undergrad.)	0.027	0.162
Father`s Ed.: professional institute (grad.)	0.033	0.18
Father`s Ed.: university (undergrad.)	0.067	0.25
Father`s Ed.: university (grad.)	0.008	0.088
Books	0.097	0.296
High expectations	0.44	0.496
Observations	100,899	

Notes: The average monthly incomes and the Family income variables corresponds to the average income received by individuals in 2012 and the family income ranges reported by parents in 2003 respectively. Years of schooling are years after Simce that the student went to secondary or tertiary education. These variables are expressed in US dollars using the 2012 and 2003 average exchange rate. 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.

As seen in Table 3, the individuals in our sample are on average 25 years old, 83% live in urban areas and 53.9% are men.

Regarding primary and secondary education characteristics: 47.6% of the sample attended a public establishment, 40.9% went to a private voucher school, and the remaining 11.4% were educated in private fee-paying schools. The proportion of private schools in our sample is higher than the overall proportion of this school in the country (around 7%). This may be because we are looking only at formal jobs. In a country with segregated education like Chile formal workers mostly come from higher quality schools and nearly all private fee paying schools fall into this category.

The family characteristics of the observed individuals show us that at the time of taking SIMCE test, most (78.1%) belonged to the lowest income group, that is their monthly family income was equal to or lower than US $434, that`s to say families with monthly incomes equal or lower than 2,6 minimum wages. This measure has to be considered carefully because it is self-reported by families and they might have incentives to under report their income.

The maximum parental education level reached is generally between primary and secondary education and most of parents (44%) expected their children to achieve high levels of education, i.e. go to college.

In 2012, the individuals in our sample earn an average monthly wage of US $782, which is similar to other data reports from Chile. Average labor wages for individuals of the same age reported by CASEN 2011, using the same exchange rate, are US $700,32.

The Chilean education is highly segregated and there are enormous gaps among students of different socioeconomic statuses. In Table 4, and in Table 8 in the appendix, it can be seen that there is a great heterogeneity in school achievements and labor performance due to the school type. As in Contreras et al. (2015), our data shows that school type has a clear impact on SIMCE scores and future wages. We can see that the students who attended paid schools have an advantage over students in public schools. It is not surprising that students who come from more privileged family backgrounds outperform their less fortunate peers.

In line with the above, Tables 11 and 12in the appendix show that the level of parental education also has a positive relationship with academic and labor outputs, reinforcing the idea that the family and school environment can determine success in Chile.

Table 4: Average Scores by School type

	Language Score		Math Score		
School type	Mean	Std. Dev.	Mean	Std. Dev.	Average Wage
Public	241.71	46.27	231.91	5.79	$727.88
Private.Voucher	255.93	46.58	249.36	54.73	$784.67
Private-Fee-Paying	269.71	47.44	274.92	59.67	$1,001.3

Notes: This table presents the mean and the standard deviation of the math and language SIMCE 2003 scores by school type.

Despite school type and family background there seems to be other important determinants of academic and labor outputs, Tables 5 and 6 show us that there is also a positive relation between abilities and wages. In particular, Table 5 shows that the higher the cognitive ability, measured by SIMCE scores, the higher future wages. Nonetheless, Table 6 shows that non-cognitive abilities are important too: there is a positive relationship between average attendance level and 2012 wages. The same applies to grades rankings and wages.[23]

Table 5: Average wage by academic achievement

Math Simce Score	Wage	Std. Dev.	Freq.
$<$200	657	403	24,161
200$-$300	763	496	59,174
300$-$400	1,007	721	17,212
$>=$400	1,621	1.020	339

Notes: This table presents the mean and the standard deviation of the 2012 wages bymath test score range. (SIMCE 2003).

Table 6: Average wage by school attendance

School attendance (%)	Wage	Std. Dev.	Freq.
$<$80	641	409	4,955
80$-$90	727	483	19,087

[23]See Table 14 in the appendix.

90$-$95	785	543	35,113
$>$95	823	567	41,744

Notes: This table presents the mean and the standard deviation of the 2012 wages by the level of school attendance (measured as a percentage) in the last three years at secondary.

Results

Our main results are presented in Table 7.

The first specification has positive signs for school type and the coefficients are statistically significant. The main conclusion of specification 1 is that there is an enormous heterogeneity between tuition and public schools, and that math test scores are more valued than language test scores in the labor market. When including our first non-cognitive measure in specification two, we observe that average school attendance from 2003 until 2006 is positive and statistically significant in explaining wages, which is intuitive since attendance is being assumed to be a proxy for persistence, responsibility, and motivation.

In specification 3 we use other non-cognitive measure: ranking of the average grades in 2003 (when they took SIMCE). Improving the relative position in the ranking increases wages by a statistically significant amount of money, which is particularly relevant in the context of low quality education.

When including both measures in specification 4, we observe that both non-cognitive skills maintain their sign and significance. Besides, attending a private voucher school when the individual was 16 years leads to a 2.56% increase in earnings in 2012 compared to individuals who attended public schools. This percentage is 6.52% for students attending private schools.

It is interesting to note that when including non-cognitive measures in the estimation the gaps between private voucher and private fee-paying against public schools grow. In other words, an individual who attended a private voucher school earns, on average, US $17 more each month than an individual who attended a public school after controlling for individual, family, and some schooling characteristics such as school type. The monthly difference for an individual attending a private fee paying compared to a public school is, on average, US $43. But, this monthly difference of private voucher and private fee paying against public schools increases to US $20 and US $51 respectively when we control for non-cognitive abilities.

In specification 5 and 6 we include relevant control variables to clean up the effect of our non-cognitive measures. When including schooling years, type of tertiary studies, work and study area and two dummies indicating whether the individual finished his secondary and tertiary studies in column number 5 we observe non-cognitive coefficients decrease but maintain their statistical significance.

Table 7: OLS Robust Estimations.

VARIABLES	(1) lnw	(2) lnw	(3) lnw	(4) lnw	(5) lnw	(6) lnw
Private Voucher	0.0222***	0.0184***	0.0286***	0.0256***	0.0174***	0.00692*
	(0.00439)	(0.00439)	(0.00438)	(0.00439)	(0.00410)	(0.00413)
Private Fee-Paying	0.0555***	0.0556***	0.0658***	0.0652***	0.0491***	0.0270***
	(0.00740)	(0.00739)	(0.00737)	(0.00736)	(0.00691)	(0.00700)
Private Voucher*Math	0.0130***	0.0121**	0.0121**	0.0116**	0.0106**	0.00845*
	(0.00483)	(0.00482)	(0.00481)	(0.00480)	(0.00441)	(0.00440)
Private Fee-Paying*Math	0.0687***	0.0677***	0.0668***	0.0663***	0.0606***	0.0565***
	(0.00761)	(0.00761)	(0.00758)	(0.00758)	(0.00693)	(0.00689)
Cognitive Abilities Proxies						
Math Simce	0.0781***	0.0748***	0.0630***	0.0618***	0.0349***	0.0139***
	(0.00381)	(0.00381)	(0.00383)	(0.00383)	(0.00356)	(0.00372)
Language Simce	0.0149***	0.0147***	0.00528*	0.00577**	0.00324	-0.00343
	(0.00281)	(0.00280)	(0.00281)	(0.00281)	(0.00263)	(0.00266)
Non Cognitive Abilities Proxies						
Average School Attendance (2003-2006)		0.00340***		0.00231***	0.000614**	0.000250
		(0.000227)		(0.000230)	(0.000242)	(0.000243)
Ranking of average grades at school			0.0602***	0.0562***	0.0335***	0.0503***
			(0.00225)	(0.00229)	(0.00214)	(0.00232)
Educational Characteristics						
Finish Secondary Education					0.0508***	0.0476***
					(0.00850)	(0.00849)
Finish Tertiary Education					0.404***	0.398***
					(0.00622)	(0.00622)
Years of Education					0.0377***	0.0335***
					(0.00195)	(0.00196)
School $\overline{Simce}$						0.0543***
						(0.00318)
Constant	9.659***	9.629***	9.896***	9.861***	9.922***	10.82***
	-1.155	-1.154	-1.154	-1.154	-1.087	-1.089
Observations	100,899	100,899	100,899	100,899	100,899	100,899
R-squared	0.146	0.148	0.152	0.153	0.271	0.274
Exogenous Characteristics	YES	YES	YES	YES	YES	YES

Family Background	YES	YES	YES	YES	YES	YES
Educational Characteristics	NO	NO	NO	NO	YES	YES
Work Area	NO	NO	NO	NO	YES	YES
School SIMCE Average	NO	NO	NO	NO	NO	YES

Robust Standard Error in Parentheses

***p<0.01 **p<0.5, * p<0.1

Specification 6 is our main specification: it includes all the above mentioned control variables plus the average Math and Language Simce by school, to clean up the effect of our cognitive measures. In this specification the coefficients for school dependence are significantly lower: attending to a private voucher school when the individual was 16 years leads to a 0.69% increase in 2012 earnings compared to individuals who attend public schools. This percentage is 2.7% for students attending private schools.

The coefficients associated to school type and academic achievement variables are reduced-form parameters. These estimates account for direct and indirect effect of early educational investment on adult earnings. Their interactive variables remain significant when including non-cognitive abilities in the estimation. This means that the estimated coefficient associated with academic achievement absorbs part of the effect of school type through a possible short-term impact on current test scores, so that the real effect on wages of attending to a private voucher and private fee paying school is on average 1.53% and 8.35% respectively.

The gap in tests scores between the different school types in Chile has already been documented. Mizala & Repetto (2011) using structural switches found that the estimated effect of private voucher education amounts to about 4-6% of one standard deviation in test scores. Contreras & Sepúlveda (2010) found that the contribution of attending private subsidized schools is 2.5 additional points on average, although without controlling for student selection criteria. McEwan (2001) also found systematic differences between school type and religious orientation on math and language achievement. In his study, students in every type of private school had higher language achievement in test scores than public school students. For example, private non-voucher students score more than one standard deviation higher than public school students.

Math test scores are statistically significant and positive: a one standard deviation increase in score (about 56 points) leads on average to 2.36% more income nine years later. These percent goes from 1.39% to those individuals that attended public school to 7.04% ($1.39% + 5.65%$) in wages nine years later, for students attending private fee-paying schools. Meanwhile, language test scores are negative and not significant in explaining wages in our estimation, which is consistent with most literature on the subject.

Experience effect on wages is positive and grows at decreasing rates. Those who finished secondary studies earn on average 4.76% more than those who didn't, and those who finished their tertiary studies earn 39.8% more than those who didn't. The average Simce of the school is positive and statistically significant. At last, one more year of education raises wages by 3.35%. All these variables are statistically significant.

In specification 6 our non-cognitive measures remain positive. In this column, average school attendance loses its statistical significance and this might happen because of the low variability of the reported attendance among students[24]. On the other side, the school grades ranking remains statistically significant and its coefficient grows. Since these variables are proxies for non-cognitive abilities, we are interested in their magnitude relative to other variables and not in their absolute value. So that we can compare the coefficients from our estimation, we standardize them. The standardized coefficients of the main variables can be seen in Table 8, in decreasing order.

Table 8: Beta Coefficients of Specification 6.

VARIABLES	Standardized Coefficient
Effective Labor Experience	0.3889
Finish Tertiary Education	0.2022
Family Income	0.1146
Men	0.1069
Years of Education	0.0922
School $\overline{Simce}$	0.0809
Ranking of Average grades at school (2003)	0.0719
Math Simce	0.0343
Private-fee-paying	0.0209
High Parental Expectations	0.0194
Urban Zone	0.0159
Finish Secondary Education	0.0145
Average school attendance (2003-2006)	0.0037
Private-Voucher	0.0031
Language Simce	-0.0049

From this table we can conclude that school grades ranking as a proxy of non-cognitive abilities is important in determining wages. Furthermore, this table allows us to conclude that non-cognitive

[24]The plot of average school attendance can be seen in graph one in the appendix

coefficients are as important as school type and cognitive abilities in explaining wages. The coefficient of average attendance represents 10.7% of the coefficient of the math SIMCE score and 17.7% of the coefficient associated with attending a private fee paying school. Meanwhile, the coefficient of the ranking of average grades is more than 2 times larger than the coefficient associated with Math test score and more almost 3.5 times the coefficient of attending a private fee paying school. Besides, the ranking represents 88.86% of the average school Simce.

The magnitudes of the ranking effect relative to attending a private fee paying school and math SIMCE are important statistically and economically. Math scores and the type of educational institution have usually been considered as the most important factors in explaining wage differences in Chile. However, a one standard deviation increase in math SIMCE score increases wages by at least 2.36% while the same change in average attendance and grade ranking increases wages by 0.25% and 5.03%, respectively. It is worth noting that a positive change of one standard deviation in grade ranking generates a bigger gap in wages than the one from school type.

These results are consistent with Heckman et al. (2006); as in the United States, in Chile there are individuals with high scores on standardized tests and poor performance on the labor market, which reflects their lack of non-cognitive abilities that are valued and prized in the labor market.

Robustness Check:

In this section, in order to check the robustness of our results we are going to present the effects of different measures of ranking on wages. In table 9 we replace our existent ranking measure in specification 6 with five new measures. In the first column, we introduce the ranking by school class. Coherently, its sign is positive and the magnitude of the coefficient is statistically not different to the school ranking coefficient presented in specification 6 of table 7. In column 2 we include a measure of persistence of the ranking, that is a discrete variable that takes value 1 if the student belonged to the 25% best grades in the school for two consecutive years and 0 otherwise. Its sign is positive and its coefficient is bigger than the school ranking and statistically different, meaning that the persistence of the outcome is more important to explain salaries than the single outcome. In column 3 we present a variation of the persistence measure. This represents the same as the measure in column 2, but for the class. It sign and coefficient is consistent with the other measures, and it is statistically not different to the school ranking persistence measure.

Improving the relative position in the ranking in one standard deviation raises wages by 5%. Belonging to the top 25% grades of the school for two consecutive years raises average monthly wages 9 years later by 10,7%.

In column 4 and 5 we introduced the residual of the estimation of ranking and persistence of the ranking against the Simce test scores. This was done in order to clean the non-cognitive part of the ranking by taking away the cognitive part of it. Both coefficients remain positive, statistically significant and are not different from the ranking measure they come from.

Average attendance might gain or loseit statistical significance when changing the ranking proxy. Private voucher loses significance when using our class persistence measure and it is not different from public school, what is consistent with many literature on the subject.The other variables of the estimation are robust and their coefficients do not change much when changing the ranking proxy.

Table 9: Robustness of the Ranking.

VARIABLES	(1) lnw	(2) lnw	(3) lnw	(4) lnw	(5) lnw
Private Voucher	0.00692*	0.00713*	0.00506	0.00692*	0.00713*
	(0.00414)	(0.00413)	(0.00414)	(0.00413)	(0.00413)
Private Fee-Paying	0.0276***	0.0282***	0.0279***	0.0270***	0.0282***
	(0.00700)	(0.00701)	(0.00701)	(0.00700)	(0.00701)
Cognitive Abilities Proxies:					
Math Simce	0.0206***	0.0207***	0.0244***	0.0248***	0.0285***
	(0.00368)	(0.00367)	(0.00366)	(0.00365)	(0.00363)
Language Simce	-0.00113	0.000141	0.000684	0.00508*	0.00589**
	(0.00265)	(0.00265)	(0.00265)	(0.00263)	(0.00263)
Non-Cognitive Abilities Proxies:					
Average School Attendance	0.000459*	0.000530**	0.000645***	0.000250	0.000530**
	(0.000242)	(0.000241)	(0.000241)	(0.000243)	(0.000241)
Class Ranking of Average Grades	0.0431***				
	(0.00221)				
Ranking Persistence within the school		0.107***			
		(0.00596)			
Ranking Persistence within the class			0.102***		
			(0.00599)		
Ranking residual				0.0503***	
				(0.00232)	
Ranking Persistance Residual					0.107***
					(0.00596)
Attendance					
Constant	10.57***	10.62***	10.48***	10.82***	10.64***
	(1.093)	(1.090)	(1.089)	(1.089)	(1.090)
Observations	100,801	100,899	100,899	100,899	100,899
R-squared	0.273	0.273	0.273	0.274	0.273

Exogenous Characteristics	YES	YES	YES	YES	YES
Family Background	YES	YES	YES	YES	YES
Educational Characteristics	YES	YES	YES	YES	YES
Work Area	YES	YES	YES	YES	YES
School SIMCE Average	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Concluding Remarks:

Cognitive and non-cognitive abilities are important in explaining wages in Chile. Using a Longitudinal data that followed 100,899 individuals through nine years of their lives from high school to labor market, allowing us to control for non-observables to get reliable estimations, we can conclude that both types of abilities matter.

The effect of cognitive abilities on test scores and wages has been widely studied. Due to the lack of data, non-cognitive research on less developed countries continues to be rare. Thus there is a part of wages that is yet unexplained. To be able to measure the effect of non-cognitive abilities on outcomes, we need to use imperfect proxies such as average school attendance and grade ranking by school. We argue that these proxies are a good measure of non-cognitive abilities because they represent persistence, responsibility, and motivation, among others. At the student level, scales measuring conscientiousness, self-control, grit, and growth mindset are positively correlated with attendance so measures of non-cognitive skills are positively correlated with student attendance. Our hypothesis states that these characteristics are valued and priced in the Chilean labor market along with cognitive abilities.

Our first result is that when adding non-cognitive measures to our estimation, the wage gaps between private voucher and private fee paying schools and public schools increase. The signs and significance of the type of school dummies and the test scores are consistent with most literature on the subject.

Our main finding is that non-cognitive abilities are important in explaining wages; they are positive and statistically significant. Furthermore, the above evidence leads us to conclude that non-cognitive skills are as (or more) important in the determination of wages as cognitive skills. One standard deviation increase in math SIMCE score is associated with 2.36% increased wages while the same change in average attendance and grade ranking is associated with increased wages of 0.25% and 5.03% respectively.

Cognitive abilities have been used to select students who enter tertiary education and thus determine their wage paths. Even though we have not directly talked about the job market or the tertiary education selection processes, our results allow us to think that a more complete selection system which considers cognitive and non-cognitive abilities, would be much more effective in matching the right person with the right job.

There is evidence that genetics play a major role in explaining the origins of the differences in human cognitive ability. This would determine differences in the performance of adults in the labor market and would limit the effectiveness of public policies towards disadvantaged populations. Also, research has found that cognitive abilities are malleable only through the first years of the life cycle and are costly to train.

Recent evidence establishes the power of other types of abilities, specifically non-cognitive ones, and a potentially important role for the environment and interventions in creating such abilities. Remember that there is evidence that this type of skills might be shaped throughout an individual's life in a cost effective way. In other words, we can say that a part of the productivity of each individual is genetically defined, but there is an important role for interventions, education, interaction with others, and work experience among other life experiences in the development of non-cognitive abilities.

Our results are particularly important for a developing country with high levels of inequality like Chile, where education is highly segregated. Improving non-cognitive abilities could be a way to compensate for this segregation. Our results leave an important scope for the action of social policy: non-cognitive abilities can be used as a policy instrument to reduce labor income gaps in Chile, and could become an important social mobility factor since they are evenly distributed among the population. Our evidence suggests that training non-cognitive skills could be as or even more effective in increasing wages than training cognitive skills and probably much cheaper (Heckman & Kautz, 2012). In conclusion, the soft part of wages could become an equalizing wage factor.

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Appendix

Table 10: Average wages by school type

	Wage 2012	
School type	Mean	Std. Dev.
Public	728	489
Private.Voucher	785	524
Private-Fee-Paying	1001	709

Notes: This table presents the mean and the standard deviation of the 2012 wages according to the type of school attended by the individuals in our sample.

Table 11: Average outputs by mother`s education.

Education level	Math Score	Language Score	Wage
Mother`s Ed.: primary	226.75	236.06	713
Mother`s Ed.: secondary	244.85	252.4	787
Mother`s Ed.: secondary vocational	253.38	259.3	802
Mother`s Ed.: technical institute (undergrad.)	270.25	271.9	863
Mother`s Ed.: professional institute (grad.)	274.91	274.38	913
Mother`s Ed.: university (undergrad.)	295.03	288.67	1,013
Mother`s Ed.: university (grad.)	301.99	295.48	1,056

Table 12: Average outputs by father`s education

Education level	Math Score	Language Score	Wage
Father`s Ed.: primary	227.25	236.63	711
Father`s Ed.: secondary	242.16	250.06	776
Father`s Ed.: secondary vocational	251.35	257.08	800
Father`s Ed.: technical institute (undergrad.)	266.76	269.77	841
Father`s Ed.: professional institute (grad.)	270.73	272.08	891
Father`s Ed.: university (undergrad.)	289.15	284.25	987

Father`s Ed.: university (grad.)	307.51	296.42	1,123

Table 13: Average outputs by parent`s expectations

Parent`s expectations	Math Score	Language Score	Wage hline
Low expectations	216.62	226.29	677
Mid expectations	229.35	239.81	744
High expectations	268.32	270.66	860

Table 14: Average wage by average grades ranking

Ranking Quantile	Wage	Std. Dev.	Freq. hline
$<$25	695	456	25,26
25$-$50	745	493	25,19
50$-$75	791	538	25,225
$>$75	898	632	25,224

Figure 1: Average Attendance Histogram