Intergenerational Mobility in Educational Outcomes: Evidence from Chile*

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March 26, 2026

Abstract

I present new evidence on trends in intergenerational mobility in a relatively high-income yet unequal developing country as Chile. I exploit within-country across-regions variations in mobility to study how strongly children's educational paths depend on family income, how mobility varies across places, and which local conditions are associated with greater upward mobility. To answer these questions, we assemble a panel that follows all Chilean fourth-graders in 2002 through the end of their formal education. Using relative and absolute mobility measures, we find large income gradients at every step: compared with children from the bottom-income group, those from the top-income group score 25-30 percentiles higher on standardized tests, are 17 percentage points more likely to complete high school, 37 points more likely to take the university entrance exam, and 38 points more likely to earn any postsecondary degree. Mobility differs markedly across regions: among low-income students, degree attainment ranges from 31% in Ñuble to 15% in Tarapacá, with the largest relative gaps in the Metropolitana region. Cross-sectional patterns point to a strong association between upward mobility and public-school quality and a concave relationship with class size; links with segregation and local income levels are weaker. These descriptive facts provide an atlas of educational mobility in a relatively high-income developing country as Chile and a basis for targeting and evaluating policies to expand opportunity.

1. Introduction

Modern societies aspire to promote social mobility, which can foster equal economic opportunities and alter the distribution of human resources (Causa and Johansson, 2011; Card

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et al., 2018). Intergenerational mobility is a key aspect of social mobility, as it reflects the extent to which a person's economic and social conditions are influenced by the economic and social reality of their parents. This topic has attracted increasing attention in the discipline in recent years (Grawe, 2010; Chetty et al., 2014; Alesina et al., 2018; Chetty et al., 2020; Carneiro et al., 2015). In fact, the last decade has witnessed a surge in the amount of research on the subject, partly due to the availability of large panel data sets that track cohorts from childhood to adulthood. This opportunity was either nonexistent or inaccessible before.

However, most of the new research has been concentrated on developed countries (Black and Devereux, 2011). For example, Chetty et al. (2014) and Card et al. (2018) examine the US context, and Carneiro et al. (2015) investigate the Norway context. One possible reason is the scarcity of data for developing countries. Some other recent works have estimated cross-country comparisons for developing countries (such as Neidhöfer et al. (2018)). But these results are, in general, not specific to each country, so they do not allow us to understand the dynamics within countries. This is problematic when we want to generalize the findings of the literature to the world. Therefore, a relevant question is whether these results are valid in other countries or contexts. In this research, I aim to contribute to expanding the existing literature to a different setting.

In the existing literature, Chetty et al. (2014) shows that there can be significant differences within a country such as the United States. Nearby localities may have very different mobility outcomes. A crucial question is what are the factors that cause these communities to have such diverse results. The study suggests that education and segregation may be important mechanisms of income transmission. Card et al. (2018) also shows that school quality is relevant, focusing on teacher salaries. Carneiro et al. (2015) emphasizes the importance of parent income timing, finding that income is more critical in early childhood rather than later. In this paper, I will not examine the timing of parent income due to data limitations.

In this paper, I study intergenerational mobility in the context of a middle-income developing country that faces high levels of inequality, such as Chile. I focus my attention on students' educational outcomes and how they are influenced by their family income. I begin by describing the intergenerational mobility at the national level. Then, I examine mobility variations across the different regions of Chile. In the final part, I explore what factors account for the heterogeneity in mobility outcomes.

Taking advantage of the rich administrative data available in Chile, I follow the cohort of students that was in fourth grade in 2002 throughout all their formal educational cycle. The cohort is composed of around 240,000 students. Using information from different sources, I construct a panel with educational outcomes until they are approximately 30 years old. This information includes parents' and family socioeconomic characteristics, students' performance in primary and secondary, their application process to the higher-education sys-

tem, and whether they graduated or not. I cannot observe, however, the student's income. Additionally, I observe the students' family income in fourth grade (2002).

To estimate intergenerational mobility, I divide the students into three categories according to their family income: the bottom 30%, the middle 60%, and the top 10% of the distribution. Then I define five measures of student outcomes that capture different aspects of educational attainment and performance. First, the scores of the students in a standardized test in tenth grade, which reflects their academic achievement in secondary education. Second, whether the student finished high school, which indicates their completion of compulsory education. Third, whether the student took the university selection tests (PSU), which shows their intention to pursue higher education. Fourth, the scores on that test, which determines their eligibility and admission to different universities and programs. And lastly, whether the student obtained a degree in the higher education system, which represents their final educational outcome and potential labor market prospects.

In line with the literature, I find that family income is a strong predictor of educational outcomes across all the measures studied. The results are robust to controlling for the initial performance of the students. For instance, students in the top income group are 38% more likely to obtain a higher education degree than students in the bottom group, even after accounting for their initial scores.

In the second part of this paper, I study the variation of the results across regions. For this purpose, I use two different measures of intergenerational mobility in education: relative and absolute mobility. The former refers to the difference in outcomes of one group relative to another, while the latter refers to the absolute outcome of a group. I find substantial variation in both relative and absolute mobility across regions. The highest relative mobility is found in Arica and Parinacota, in the north of Chile, while one of the lowest is in the Metropolitan region, in central Chile. For instance, students from the top-income group are 18.2% more likely to obtain a degree than students in the bottom-income group in Arica and Parinacota. The same relation is 44.8% higher in the Metropolitan region. In terms of absolute mobility, the results are also heterogeneous. For instance, a student from the bottom 30% has a probability of obtaining a degree of 31.1% on average in Nuble, in the centre-south, and of 14.9% in Tarapaca, in the north.

In the third part of this paper, I study the local characteristics that could explain the high heterogeneity of results in the country. I examine the association between mobility measures and various indicators of local conditions, such as school quality, income levels, segregation, and inequality. I find evidence of a strong and positive correlation between the quality of the public schools and the mobility measures, suggesting that improving public education is a key factor for enhancing intergenerational mobility in education Chetty et al. (2014). I also find a positive correlation with income levels, indicating that regions with higher average income tend to have higher mobility, possibly due to the presence of more

barriers and disadvantages for low-income students. This differs from the evidence showed in (Chetty et al., 2014), where no effect is found. However, I find no evidence of a significant relation between school and residential segregation or inequality, which is surprising given the previous literature that has highlighted the role of these factors in shaping educational opportunities and outcomes (**?**).

Chile is an interesting country to study for three reasons. First, it is a middle-income developing country that, unlike others, has a large amount of information available that, when compiled, can be used to follow people through the first part of their lifetime. As discussed above, such a study would contribute to understanding mobility in different contexts. In particular, it will show how it can vary in relation to developed countries such as the United States or Norway, where similar studies have been performed. Second, like other developing countries from the Latin America Region and the world, Chile is characterized by high inequality, which could also be correlated with social mobility (Chetty et al., 2014). In fact, the literature has found evidence of a negative relation between inequality and social mobility (Corak, 2013). Third, Chile underwent a significant social uprising process at the end of 2019, like Colombia in 2021, and Ecuador and Argentina in 2019. The upheaval was strongly related to the perception of inequality and lack of opportunities in these countries. Understanding and improving social mobility could also help enhance social cohesion. An open question in the literature is how high inequality (and lack of opportunities) is related to high social instability.

This paper is closely related to Chetty et al. (2014), which examines the geography of intergenerational mobility in the United States using tax records and census data. I perform a similar analysis but study different educational outcomes in the context of a middle-income and highly unequal developing country, using administrative data from various sources. The general results are broadly consistent across both papers. There is evidence of important heterogeneity of results within the country, with some regions exhibiting higher mobility than others. The relative and absolute measures are correlated. And school quality is important to explain the differences across localities, as regions with better public schools tend to have higher mobility rates.

The organization of this paper is as follows. In Section 2, I define the measures of intergenerational mobility and discuss the concepts of relative and absolute mobility. In Section 3, I present the relevant characteristics of the Chilean education system that are important to understand the results of this paper. In Section 4, I describe the data used, which consists of administrative records from various sources that allow me to follow a cohort of students throughout their educational trajectory. In Section 5, I characterize intergenerational mobility at the national level using different outcomes. In Section 6, I explore the mobility measures at the regional level, and find substantial variation across regions. In Section 7, I correlate the geographic heterogeneity of mobility with local characteristics, such as school

quality, income levels, segregation, and inequality. I conclude in Section 8 with a summary of the main findings and some policy implications.

2. Measures of Intergenerational Mobility

The discussion about intergenerational mobility relies on understanding and measuring how the social and economic opportunities that a person faces are conditioned by her family and social status. Empirically, studies often use the labor and educational outcomes of a person as proxies of social and economic opportunities, and family income, social status, or education as proxies of family social status. However, these proxies may not be precise, as the labor or education outcomes of a person could differ from her actual opportunities. Chetty et al. (2014) exemplify this with the case of a person from a wealthy family who may choose not to work and dedicate herself to a different activity, or indeed work, but in a lower-paying job, knowing in both cases that she has the economic support of her family. This would reduce income persistence but, in practice, have no effect on the persistence of the underlying opportunities she faced.

I analyze the persistence of income in terms of educational outcomes. It is well documented that education is an important measure of the social opportunities that a person faces (Arrow et al., 2018; Bathmaker et al., 2016). First, it is strongly related to labor outcomes such as income and employment status. For instance, on average, people who go to university have better wages and lower unemployment rates (**?**). Second, it is also related to the beneficial social network in which a person eventually participates (**?**). And third, it is strongly related to the social capital that a person could acquire (**?**). A more complete research could also include income, as well as other labor outcomes. However, I have no access to data sets that include family income in the context of what I am studying. This could be a potential future research idea. Therefore, in this document, I characterize intergenerational mobility as the degree to which the educational outcomes of people are determined by their family income.

Chetty et al. (2014) propose two classes of intergenerational mobility: relative mobility and absolute mobility. Relative mobility refers to the outcomes of children from low-income families relative to the outcomes of children from high-income families (Black and Devereux, 2010). Absolute mobility refers to the outcomes of children from low-income families in absolute terms.

2.1. Relative Mobility

The standard measure of relative mobility in the literature is the Intergenerational Income Elasticity (IGE), which refers to the elasticity of a person's income relative to their family

income. However, since I cannot observe the income of the person, I use an alternative measure of intergenerational mobility that relates family income and the child's educational outcomes. Let Y_i be an educational outcome of the student i and I_i be the family income of the student i in her childhood. Then, the intergenerational mobility relation measured as a semi-elasticity would be given by γ in the following equation:

$$Y_{it} = \theta + \gamma log I_i + \zeta i$$

An alternative measure followed in this paper relies on defining different groups of family income allowing for a non-lineal relation between income and outcomes. As relative mobility is usually measured as the results from a group relative to another, the mobility coefficient could be estimated from a comparison between different income categories. Let G_p be a vector of dummy variables that take the value of 1 if the student belongs to the group income p, and 0 otherwise; where $p = 1, ..., P$. Therefore, in the equation (1) β_p is a relative mobility measure that indicates the difference in results between the students from the family income-group $p \neq 1$ and the base income-group $p = 1$:

$$Y_{it} = \alpha + \sum_{p \neq 1} \beta_p G_p + \varepsilon_i \tag{1}$$

In this work, I focus most of my attention on the difference between students from families in the top 10% of the income distribution and students from families in the bottom 30%. In other words, on the outcomes that low-income students have in relation to the top-income students. A higher β_p would imply a stronger relation between income and the educational outcome and, therefore, a lower relative mobility. This measure is relevant for understanding the degree of inequality of opportunity in society, as it reflects the extent to which the educational success of a child depends on their family background (Corak, 2013).

2.2. Absolute Mobility

The absolute mobility measures seek to understand the outcomes that a person can achieve conditional on their parent's income. I study primarily the outcomes of students from low-income families. Following Chetty et al. (2014), this specific measure is called upward absolute mobility, because it measures the average outcomes that low-income students can achieve in their educational cycle. Let us assume that the base income category (G_1) in Equation 1 is the one at the bottom of the income distribution, or in other words, the group of the poorest students. Then, a measure for the average absolute mobility would be α. This measure is useful because it can be used to make comparisons in terms of low-income outcomes between different regions or localities.

In this paper, I focus my attention on the upward absolute mobility measures for students from families that are in the bottom 30% of the income distribution.

3. Chilean Educational System

Chile has an educational system made up of four levels: preschool, primary, secondary and higher education. Education is compulsory starting in primary and finishing in high-school (or secondary). Primary education goes from first to eighth grade of basic education, and secondary education from first to fourth grade of secondary education. In the higher educational level, there are three types of institutions: technical training centers (CFT), professional institutes and Universities. CFT are vocational educational centers in which students can get a technical degree in two-year programs. In professional institutes, students can get a technical or professional degree without a bachelor's degree. Finally, the Universities deliver professional titles with the degree of bachelor (four years), master (one or two years) or doctorate (four or more years).

The Chilean educational system is a mixed-ownership system in which the State and the private sector participate. Preschool, primary and secondary education have three types of schools based on their of their *dependence* (or type of ownership): public, voucher, and private. Public schools are owned by the State, which fully finances them. Students do not have to pay to receive education at these institutions. These schools are administered by the municipal governments of each region of the country. Voucher schools are jointly owned, one part belongs to private individuals or organizations, and another part belongs to the State. The state subsidizes a part of the tuition fee and families must pay the other part (the only exception is those schools where the copay is 0, which are a minority within the system). These schools are privately run by the owners and the state has not participation in it. In fact, those schools were allowed to select students on the basis of their merits or other family characteristics[1]. Finally, private schools are privately owned and run entirely by their owners. Students pay the entire tuition fee. In 2011, the distribution of student attendance was 45% in public schools, 48% in voucher schools, and 7% private schools.

Academic performance is measured at the national level through the SIMCE standardized test. Its goal is to measure the quality of education in different stages at the primary and secondary level. SIMCE assesses students' learning in reading and mathematics. In primary, students generally take the test in fourth and eight grade, while in secondary, they take it in second grade. Regardless, the exact grade level at which the tests are generally administered has changed through the years. This test is mandatory for all students of the Chilean educational system in the grades mentioned above.

[1] In 2016 a new law was approved and ended the copay and selection in schools that received public funding.

On the other hand, despite the fact that education is compulsory from primary to twelve grade (fourth grade of secondary), there are still students who do not graduate. Dussaillant (2017) found that 88% of Chilean students have completed secondary education. This percentage is above the average of 85% in OECD countries. Regarding school dropouts, 10.4% of students drop out school between the ages of 15 and 19. Students who drop out tend to come from families in poverty, and often drop out due to financial problems, or for cultural, geographic or family reasons. 14% of students who drop out come from the bottom two income percentiles, while 2% come from the two highest income percentiles.

In addition to the degree of independence, there are other ways to stratify secondary education schools. Schools could be either scientific-humanist or vocational education schools. The former ones prepare students to enter a higher-education program. The later ones prepare students enter directly into the labor market, giving them a middle-level technical degree. In practice, this degree is not strongly valuated in the labor market Meller and Brunner (2009). On average, students in this type of school have a lower performance and more often tend to come from low-income families than students in scientific-humanistic schools.

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Students who finish high school have the option of entering higher education through the university selection test (PSU). The PSU is a standardized test that measures the knowledge learned until the student finishes high school. The PSU has two compulsory test and two electives. The compulsory test are reading and mathematics, while the electives are Chilean and universal history, and science (physics, chemistry and biology). The weighted-score of the students (which also includes the high-school grades and ranking) is used to apply to the programs of the universities attached to the admissions system (all public universities, traditional private universities and most non-traditional private universities). The weights in each item/test are program-university specific. A few private universities have their own mechanisms for entering to their programs. On the other hand, PSU is not required to enter to professional institutes and CFT. Some scholarships and credits available for students to study in universities require a minimum average score in the math and reading sections. To take the PSU test, students must pay an initial fee of around $40. But students from public and voucher schools and students from vulnerable socioeconomic background in private schools receive a scholarship to subsidize the entire fee of the test the first year that they are eligible to sit for the exam. The scholarship is not available in later years.

4. Data

To perform the intergenerational mobility analysis, I use data from various sources arising from the Chilean educational system. These sources allow me to reconstruct both the student's family income and a set of outcomes throughout their educational cycle. These sources include test scores and socioeconomic surveys from SIMCE, public records from the Education Ministry, PSU test results, and higher-education graduation record from DEMRE.

I present a detailed description of the sample and how the final data-set was constructed. Then, I define the relevant variables that are used in this study, presenting summary statistics for each one.

4.1. Data Construction

Recall that to perform a study about intergenerational mobility it is necessary to have, at least, information about the students' family income and a set of outputs related to the students´ performance. Taking advantage of the quality of the educational data available in Chile, I am able to follow a cohort of students from primary school to the end of their formal studies. The cohort studied was in the fourth grade of primary in 2002, students who in general were born between 1991 and 1992. This cohort was pick because it is the one that is possible to observe the longest time and that has all the relevant information available. The cohort has around 241,000 students with valid information.

I first observe the cohort in 2002, when they were in fourth grade. In that year, students had to take the SIMCE tests. As mentioned in section 3, SIMCE tests are standardized tests that are mandatory at the national level. They measure the learning process of students, and are taken in different points of their primary and secondary education. As part of the process, students, family and teachers have to answer a questionnaire that includes questions about socioeconomic characteristics (answered by the parents) and the educational learning process (answered by teachers and students). One of the questions in the family questionnaire is, in fact, the family income. This is the variable that is used in this study as measure of the family income. One advantage of this approach is that parents do not face incentives to lie in these questions, because their answers in the survey do not have any consequences in terms of scholarships, benefits or something related. In this sense, the downside related to measuring income through self-reporting is diminish by the fact that there are not incentives to lie. In the following section, I present a robustness exercise for this measure. Other variables that are observed from the SIMCE are the education of the parents (or guardian), the student performance in the standardized test and interactions inside the classroom (school climate, teachers' involvement, students' motivation, among others).

After fourth grade, I observe the academic outcomes of the students in each year through

their primary and secondary education using the performance and attendance data from the Ministry of Education. This data includes the annual performance, attendance and dropouts from the educational system. Annual performance is a useful measure within class but is not comparable across schools (or even classes), because the qualification instruments vary from one school to another or from one teacher to another. Attendance could be useful, but the reported data by the ministry tends to be noisy. This is probably derived from the fact that schools receive the government payments for each student conditional on their attendance, so they have incentives to mark as present students that are not.

I observe again an important proportion of students from this cohort taking the SIMCE test in tenth grade (or second year of high-school). A small fraction, however, did not take the test. Students might not take the test because they were absent on the test day (for instance, because they were sicks), or because they were not in tenth grade with their former classmates as some students had to retake some grade level, or because they abandoned the formal educational system (dropout, travel, death, or other reasons). It is important to mention that students do not face any individual consequences from their test results and, indeed, their results are private; and are only reported in an aggregated level. Students that assisted to school in the test days must take the test.

Then, years later, it is possible to observe if the students graduated from high-school in some point before 2020, the last record available. To do this, I use the graduation records from the Education Ministry information.

I also observe whether the students take the PSU test after high-school. A more extensive discussion about the incentives of taking the PSU can be found in section 3. If they take the test, I observe their scores and complementary information regarding their socioeconomic status. This information is directly related to benefits in the higher-education period and, thus, are not completely reliable.

Lastly, using information from the Education Ministry, I observe if the students graduated from some higher education institution, including CFTs, professional institutes, and private and public universities. As the previous cases, I observe these records until 2020. I know that most of this generation graduated high-school in 2010. Thus, many of them enter the higher-educational system in 2011 or 2012. If they attended CFTs those students should have graduated in 2 years, while if they attended a standard grade in a university they should have graduated in 5 years. I observe data for 10 years after the high-school graduation, meaning I probably observe most of the students that would eventually receive a higher-education degree in some point of their lives. There exists a subgroup within this cohort, however, that eventually will obtain a degree after 2020.

4.2. Variable Definitions and Summary Statistics

4.2.1. Family Income

As discussed above, the family income variable is defined using the family answers to the questionnaire from the SIMCE test in fourth grade. The families are asked to report the total available income in the household. Families auto-report could be considered unreliable, as families might have incentives to lie to obtain some benefits; however, in the SIMCE case this is a minor concern because the reports are not related to any kind of records related to social benefits. In table 1 the income distribution from SIMCE is presented. The same income brackets that SIMCE has on their questionnaire are presented. All the money is expressed in US dollars equivalent for the period. From the table, the 66% of the family incomes are concentrated in the first two income brackets, that is, below $282. The top 10%, on the other hand, has an income above $845.

Table 1: Family Income Distribution 4th grade

	Freq.	Perc. (%)	Cum.
Less than 141	75,717	31.4	31.4
Between 141 and 282	83,842	34.8	66.2
Between 282 and 423	30,274	12.6	78.7
Between 423 and 563	14,189	5.9	84.6
Between 563 and 704	8,275	3.4	88.0
Between 704 and 845	5,659	2.3	90.4
Between 845 and 1,127	5,952	2.5	92.8
Between 1,127 and 1,408	4,580	1.9	94.7
Between 1,408 and 1,690	2,828	1.2	95.9
Between 1,690 and 1,972	1,832	0.8	96.7
Between 1,972 and 2,254	1,425	0.6	97.3
Between 2,254 and 2,535	1,272	0.5	97.8
More than 2,535	5,313	2.2	100.0
Total	241,158	100.0	

As a robustness check, I compared the income distribution derived from this survey with the income distribution from the national socioeconomic survey data (CASEN) in the two closest years, 2000 and 2003. On each CASEN, I construct a sub-sample of families with children of similar ages. The monthly family income distribution from the three data-sets are very similar (see figure 1).

4.2.2. Students Outcomes

To analyze the mobility, I focus my attention in the educational cycle. In that sense, seven outcomes in different points within the cycle are defined. In chronological order, I study the SIMCE math and reading results in tenth grade; whether the student completed high-school; whether the student takes the PSU test; the PSU test score; and whether the student obtains

a higher education degree.

The first set of two variables are the SIMCE math and reading tests in tenth grade. They measure the learning outcomes obtained from students until tenth grade. They are relevant outcomes because deliver comparable information regarding student performance. The test scores are comparable between students in different schools. I normalize the scores to percentiles of performance. In doing so, it is possible to better compare across different tests. By construction the average percentile is 50. However, the performance is not equally distributed among original schools (the type of school that student attended in fourth grade). Students in private school achieve on average the 80% percentile, while the ones in public schools achieve only the 41%.

The third variable refers to finishing high-school. It takes the value of 1 if students finish high-school in some point before 2020, and 0 otherwise. On average a 88% of the students in the cohort finished high-school. This distribution is not equally distributed among (origin) schools. A 97% of the students in the private schools have records of finishing the secondary education, while an 92% and 84% in voucher and public schools respectively.

The third variable refers to finish high-school. It takes the value of 1 if students finish high-school in some point until 2020, and 0 otherwise. Students may finish high-school in the regular system, or, if they dropped out and want to return, in the adult education system. For this paper, I do not take into account the system where they finish. Thus, if they obtained a degree before 2020, the variable takes the value of 1. On average an 88% of the students in the cohort finished high-school. This distribution is not equally distributed among (origin) schools. A 97% of the students in the private schools have records of finishing the secondary education, while an 92% and 84% in voucher and public schools respectively.

The fourth variable refers to taking the PSU. It takes the value of 1 if students take the PSU in some point until 2020, and 0 otherwise. Students may take the test at any point after finishing high-school, but receive a scholarship that cover the test fee if they take the test immediately after finish high-school. This variable is relevant because it reflects additional information regarding the student that other variables do not capture. As there are no monetary costs to taking the test for low-income students and the test results have a random component such that the results could be higher (or lower) than the expected conditional on the student performance[2], students have rational incentives to take the test. Therefore, students may not take it because either (i) they do not want to study in the higher education system; or (ii) they believe take the test is worthless conditional on their performance. A student´s school, teachers and classmates could be important in determining his/her decision. On average a 72% of the students in the cohort take the PSU. The percentage, however, dif-

[2]Let PSU_i be the student score in the PSU test, X_i a set of characteristics of the student and ϵ_i a random variable. The student score could be expressed as a linear approximation given by $PSU_i = \gamma X_W e + \epsilon_i$. Students may know the γX_i component, but the actual realization of ϵ is unknown for them before the test.

fers greatly among (origin) schools. A 96% of the students in the private schools have taken the PSU, while an 80% and 63% in voucher and public schools respectively. These statistics reinforce the idea of the importance of the school and peers in the confidence and shaping the decision to take test.

The fifth and sixth variables are the PSU scores in math and reading. I consider these scores because they deliver a new measure of academic performance, which is also, the last available. While the SIMCE does not have individual consequences for the students, PSU determines in an important way the student´s application in terms of program and institution they may go to. As discussed in section 3, an important fraction of the universities participate in the common admission system (all the public and the majority of private institutions). This system is unified and establishes that institutions can only consider in their admission processes PSU scores and student grades in high-school.[3] Thus, if a student has a lower performance, his/her chances to study in a university are diminished and, eventually, could only access private universities outside the admission system or to other types of institutions such as CFTs or Professional Institutes. The scores are normalized in terms of percentiles of performance as in the case of the SIMCE tests. By construction the average percentile is 50. However, as has been discussed, the performance is not equally distributed among (origin) schools. Students in private school achieve on average the 80% percentile, while those in public schools achieve only the 40%, like the SIMCE test case.

The last and most important variable is whether the student obtains a degree from a higher-education institution. I consider that this is the most important variable in the analysis because (i) it measures the last step in the educational system, that is a result of the student-specific trajectory; (ii) it considers, also, alternative trajectories to the academically focused one, more reflected in variables such as SIMCE and PSU test results, because it considers students obtaining any type of degree, even a technical one; and (iii), most important in terms of this paper objective, is strongly related to the future trajectory of student´s income (Avery et al., 2006; Hoxby et al., 2013; Manoli and Turner, 2018; Deming and Dynarski, 2010). A more precise definition of the variable is whether the student obtains a degree before 2020, around 10 years after most of the cohort graduated from high-school. On average a 38% of the students in the cohort have obtained a degree by 2020. The percentage, however, differs greatly among (origin) schools. A 66% of the students in the private schools have received a higher-education degree, while a 43% and just a 29% have in voucher and public schools respectively.

[3]There are a small number of special admissions such as quotas for low-income students, sport quotas, among others.

5. National Results

The analysis of Intergenerational Mobility starts by characterizing the relationship between parent income and children's educational outcomes at the national level. These results are baseline estimates of relative mobility and show the differences between students from high-income families and students from low-income families in educational attainment. Then, I discuss how the mobility measures change when the differences in initial student performance are considered.

5.1. Baseline Estimates

To study the relationship between family income and student performance, I analyze the relation between income and a set of outcomes in different stages of the educational cycle. As measure of income, I consider the child's family income in fourth grade. Then, I define five main variables of educational attainment. The first variable is SIMCE performance of students in tenth grade, focusing in the Math and Reading tests scores. The second variable is the probability of finishing high-school. Even though competition of high-school is mandatory in the country since 2003, there is still some degree of dropout. The third variable is the probability of sitting for the University Selection Test (PSU), commonly used and required for the process of applying to universities. In addition, I also consider as the fourth variable the PSU scores themselves, which greatly determines the program an university that the prospective student can apply to. As with SIMCE scores, I again focus on the math and reading scores. Finally, the last variable is the probability of obtaining a degree from a higher-education institution. With these five variables I can map student's educational cycle, and observe how family income influences educational attainment at each stage. A low correlation with these variables serves as evidence of higher mobility as the student performance is explained by other factors other than the income of their families.

To simplify the analysis, stratify student by family income into three broad categories: bottom, middle and top. The bottom income group includes all the students from families in the bottom 30% of the income distribution. The middle-income group includes all the students from families in between the 30% and 90% of the income distribution. The top income group includes the rest of students from families in the top 10% of the income distribution.[4] Therefore, I can make comparisons in the performance of the students in the bottom-income group in relation to the students in the middle and top incomes group.[5] Let's consider Y_i as

[4]Given that the income is measured in brackets, the percentiles are approximations. Thus, the bottom 30% is exactly the bottom 31.4%, the middle group is exactly between 31.4% and 90.4%, and the top 10% is exactly top 9.6%.

[5]Onwards, the expression *students in the top-family income group* and *students in the top-income group* are used indifferently.

the educational outcome of student i, and G_i^x as a dummy variable that takes the value of 1 if the student i belongs to the group $x = top, middle, bottom$, and 0 otherwise. Thus, I can estimate the following equation:

$$Y_i = \alpha + \beta_1 G_i^{top} + \beta_2 G_i^{middle} + \varepsilon_i \quad (2)$$

Where β_1 and β_2 are the relative performance of students in the top and middle-income group, respectively, in relation to the students in the bottom income group. α is the absolute performance of the students in the bottom-income group. $\beta_1 = 0$ would imply that there is total mobility, students from the bottom-income group have no difference with students in the top-income group in terms of their educational outcomes and so income is not a factor determining educational attainment. $\beta_2 = 0$ but $\beta_1 \neq 0$ would imply that students in the bottom and middle income groups have a similar performance on average, but different from the top income group. Therefore, in a more meritocratic society, understood as a society with more opportunities and higher intergenerational mobility, β_1 and β_2 should be close to zero.

In table 2, I present the results from the OLS estimation of equation (2). Column (1) and (2) show the correlation between family income and SIMCE scores. As discussed above, the comparison group is the students from the bottom-income distribution group. The SIMCE scores are expressed in percentile of the score results. The results are robust to use raw scores or standard deviation units. Given that students may not take the test for non-random reasons (because they had to repeat a grade, for instance), I use a Heckman selection model to control for the potential selection implicit. As selection variable, I use the SIMCE scores in fourth grade. Then, the results in the first two columns are the second stage in the selection model. It could be seen that students in the bottom-income distribution performed worse than students both in the middle and top-income groups. In fact, people in the top income distribution were, on average, 24 percentiles higher on the score distribution than people in the bottom-income group; while people in the middle-income group were, on average, 8 percentiles above the bottom-income students. Reading and math scores show reasonably similar patterns in terms of the correlation measured.

Column (3) shows the correlation between family income and the probability of finishing High-School. As discussed in the section 3, high-school graduation is compulsory. However, although the completion rate is high, there are still a small percentage of students who dropout before graduating. This percentage is not homogeneously distributed across income groups, as expected. Most dropouts are found in the bottom of the income distribution. To simplify the analysis, the coefficients of the LPM are reported. The results are consistent and robust using instead a Probit Model. The coefficients for both income-groups are statistically significant. Students in the top-income group have a higher probability of finishing high-school with respect to their counterparts (around 17% higher than students in

the bottom-income group). Students in the middle-income group also have a higher probability of finishing high-school than the students in the bottom-income group (around 13% higher). The coefficients of the two income-groups are statistically different between them; but from all the studied outcomes, the difference is the smaller. In that sense, the coefficient associated with top-income group students (β_1) is 1.3 the coefficient for middle income students (β_2) (this ratio β_1/β_2 is, for instance, around 2.9 in the SIMCE math and reading scores).

Column (4) shows the relation between family income and the probability of sitting in for the PSU tests. As discussed in section 3, students can take the PSU after finishing high-school (most people take it between the first two years after high-school graduation). This test is required to apply to many higher-education institutions. This includes public universities, traditional private universities and some non-traditional private universities. To apply to the first two groups the PSU is required, and the students are admitted based purely on their PSU scores and their high-school grades (programs could have different weighting between the four tests and high-school grades). In the other hand, there are also some non-traditional private universities that do not require the PSU at all. Professional institutes and CFTs also do not require the PSU. In order to take the PSU test, students must pay an initial fee of around $40. But students from public and voucher schools plus students from vulnerable socioeconomic background in private schools receive an scholarship to cover the entire test fee. Students that did not take the test immediately after graduating and try to take the test in the following year, cannot receive this scholarship and must pay for the test. Thus, there is a strong incentive to take the test in the year first year, particularly for students from low-income families which will thereby face no major monetary costs to attempt the PSU. This context suggests that the main reason for not taking the test is related with students future prospects and self-esteem. If students do not want to continue their studies, they are less likely not take the tests. If students do not believe that they can obtain a good result in the tests and, therefore, believe that participating in the process will bring them no real benefit, they are less likely to take the test. The results in column (4) show that the relation between family income and the probability of taking the PSU is positive and significant. Students in the top-income group are, on average, 37% more likely to take the PSU test than students from the bottom income-group. Students in the middle group are also a 23% more likely to take the test than students in the bottom-income group. The difference between both coefficients is statistically significant, and the ratio β_1/β_2 is around 1.6 (against 2.9 in SIMCE and 1.3 in finishing high-school).

Columns (5) and (6) shows the estimation of the correlation between family income and PSU scores. As in the case of the SIMCE test, this estimation present the additional challenge related to potential selection bias. In fact, the selection seems to be much higher in this case, because students may decide not to take the test based on their preferences and character-

istics. I control for this potential selection using a Heckman selection model. The exclusion variable used is the SIMCE scores in 2002. The coefficients are the second stage of the estimated model. The PSU scores are expressed in terms of percentile of achievement to improve the ease of interpretation and comparisons. The results are robust to use raw scores or standard deviation units. Students from the top-income group tends to be around 28 percentiles above students from the bottom-income group. Students in the middle-income group are, on average, 9 percentiles above those students in the bottom group. The difference between both coefficients is statistically significant, and the ratio β_1/β_2 is around 3.2, the highest among the different variables analyzed. In other words, students in the top-income group have on average a higher performance in PSU than students in the middle-income group, and that difference is the biggest difference among the variables studied. Another interesting finding is that the coefficients are relatively higher than in the SIMCE case, which implies that the family income effect is increased as the student advances through her educational cycle.

The last column shows the correlation between family income in fourth grade and the probability of obtaining a degree from a higher-education institution. The degree could be conferred by a vocational/professional institution or a university. Given the data, I am able to observe if the student received a degree prior to the end of 2020, which is equivalent to ten years after the cohort should have graduated from high school if the student education was uninterrupted. It is worth pointing out that university programs in Chile last, in general, between 5 and 6 years, while vocational programs last 2 years (see section 3). Therefore, it is expected that a high proportion of the students that would obtain a higher-education degree in some point of their lives, would do so within our 10 years. However, there is a small fraction of students that could still graduate outside this time span. Thus, another way to define the variable is the probability of obtain a higher-education degree before being a 28-29 years old. The results show evidence that students from the top-income group are a 38% more likely to obtain a higher-education degree than students in the bottom-income group, while the students from the middle-income group are a 18% more likely respect to the students in the bottom-income group. The difference between both coefficients is statistically significant, and the ratio β_1/β_2 is around 2.1, lower than difference in scores, but higher than the difference respect to finishing high-school or taking the PSU. An important finding from these results is that while the difference of the bottom-income group with the middle-income one is reduced with respect to the differences in terms of probability of take the PSU, the difference with the top-income group stays similar (0.37 and 0.38). This suggests that, although some intermediate outcomes in the education cycle of students could be less related to income, in the end the probability of obtaining a degree is highly sensitive to family income (belonging to the top 10% of the family income distribution in childhood).

The above results imply consistently that in Chile the family' income in the childhood is

Table 2: Baseline Estimates

	(1) SIMCE Math	(2) SIMCE Reading	(3) Finished High-School	(4) Took PSU	(5) PSU Math	(6) PSU Reading	(7) Degree
Middle Income	8.40***	7.00***	0.13***	0.23***	9.26***	9.40***	0.18***
	(0.15)	(0.15)	(0.00)	(0.00)	(0.16)	(0.16)	(0.00)
Top Income	24.66***	21.00***	0.17***	0.37***	29.54***	28.27***	0.38***
	(0.21)	(0.21)	(0.00)	(0.00)	(0.21)	(0.21)	(0.00)
N	223425	223089	241158	241158	201643	202247	241158

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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a strong predictor of the child performance in her future life, even that far as in the probabilities of obtain a higher-education degree. A child that comes from low-income family, have very little opportunities to achieve good educational results compared to other children. But also, the evidence shows that a child from the top 10% of income distribution is more likely to obtain better results in all outcomes. Those differences are not only strong respect to the low-income students, but also respect to middle-income ones. In fact, the difference between the top-income group and the middle-income group is higher than the difference between the middle-income group and the bottom-income group.

Given the importance of education (Carneiro and Heckman, 2003; Heckman, 2006; Arrow et al., 2018), is expected that students that had less educational opportunities through their lives would also have worst outcomes in the labor market. Indeed, in Chile, people with higher-education degree earn 157% more than people without it (Carrillo et al., 2018). Ultimately, these results shows that in Chile the results that a child could achieve are strongly related with his/her family's income, and thus, that there is low mobility in relative terms.

It is worth mentioning as a precautionary note that these results are not the complete picture of intergenerational mobility, because it lacks of the last and important part referred to the future student income. In that sense, an future research project could include the differentiation between graduation from high-quality universities and low-quality universities, and high-income and low-income degree, which are also strongly related to the student's future income.

5.2. Estimates by Student Performance

The results in the previous subsection are baseline estimates that compare the relation between the three income groups and the different outcomes through the educational cycle. Now in this subsection, I present results that also include the relative performance of students in their childhood. Thus, I try to answer what are the relative results of students

from the bottom-income group that had a high performance in their childhood with respect to their counterparts from the top income group; or what are their results with respect of students from the top-income group, but that had a low performance in their childhood. In a more meritocratic society, or high intergenerational mobility, would be expected that students from the bottom-income group and high-performance achieve better results than those students from the other income groups that had worst performance.

In the following I separate the students in three performance groups. High-performance, middle-performance and low-performance. The groups are defined based on their relative rank in the SIMCE in fourth grade. Then, I define nine groups that are the result of the combination of the three income groups and the three performance group, bottom-income and low-performance, bottom-income and middle-performance, bottom-income and high-performance, and so on. Let now $G_i^{x,p}$ be a dummy variable that indicates whether the student i belong to the group defined by the combination between the sub-group of income $x = top, middle, bottom$ and the sub-group of performance $p = high, middle, low$. Then, I can estimate the following equation:

$$Y_i = \alpha + \sum_p \beta_p G_i^{top,p} + \sum_p \gamma_p G_i^{middle,p} + \sum_{p \neq low} \theta_p G_i^{bottom,p} + \varepsilon_i \tag{3}$$

Where the omitted category is the group of students that belong to the bottom-income and low-performance group.

I estimate equation (3) using two alternative definitions for the students performance groups. First, I use the student performance in the national distribution. And then, I use the student performance respect to her income group distribution. The following two subsection explore each definition.

5.2.1. Student Performance in the national distribution

This subsection analyzes the relation discussed in equation (3), constructing the performance groups using the national score distribution in fourth grade. That is, all the students are ordered from low to high performance and are divided in three groups with equal size. Using this definition, I build the nine subgroups of income and performance, from the bottom-income and low-performance group to the top-income and high-performance.

With the above definition, the estimation of equation (3) allows me to find a relative mobility measure conditional on student performance. High performing students have a similar performance across groups, but they are different in terms of income. In a perfectly meritocratic world, the differences should be zero among students from different income groups inside a particular performance group. The students' outcomes should be related only to its past performance, and not to their family income. In an imperfect meritocratic world, the differences between groups conditional on performance should be relatively lower. An in-

teresting metric to discuss is the difference between high performance and low performance students across the income distribution. We would expect that high performing students have better results than low-performing students both within and across income groups. That is, for instance, high performing students in the bottom-income group should have relatively better results that low performance students in the top-income group. In other words, in a semi-meritocratic world, the students with the best performance among the low-income group should have better results than students with the worst performance in the wealthy group.

In table 3, the previous estimations are re-explored equation (3) using the discussed performance subgroups. Column (1) and (2) show the estimation for SIMCE math and reading, from it I can glean two major findings. First, it could be seen that conditional on performance groups, the relation between income groups remains similar and consistent with the results from the baseline estimations. That is, for each performance group, the students from the top-income group have on average better SIMCE results than their classmates, and middle-income group students have better results than the bottom-income group students. For instance, For instance, within the low performance group, top-income students are on average 14.5 percentiles above low-income students in the SIMCE math scores; percentiles above low-income students in the SIMCE math scores, while middle-income students are on average 4.2 percentiles above. Within the high-performance group, top-income students are on average 47.2 percentiles above in the math section with respect to their counterparts in the bottom-income group ($\beta_{high} - \theta_{high}$). The results are consistent for both math and reading. Second, high performance students in the bottom-income group have better results than low performance students in the top-income group (coefficients in the math test of 36 and 13.9, respectively). This difference is statistically significant in both tests. These results imply that high performance students still achieve better results than low performance students, even when they belong to the bottom-income group. In fact, the outcomes of high performance and low-income students is close to the performance of the medium performance and high-income subgroup, and superior to the attainment of the medium performance and middle-income subgroup.

In column (3), the probability of finish high school is explored and I can also glean two main findings. First, conditional on performance groups, the relation between income groups is less consistent than the results from the baseline estimation. For instance, low performance students in both middle and top income-subgroups have a higher probability of finishing high-school than students in the bottom-income group, but similar between them (13% and 12% respectively). AsOn the opposite end, high-performance students have an increasing relation versus the baseline estimations (top-income students have better results than middle-income, and middle-income have better results than low-income; or, equivalently, $\beta_{high} > \gamma_{high} > \theta_{high}$). This could be explained by the fact that, as high-school

education is mandatory, both medium-income and top-income groups have similar results, which are close to 0.95 (95% graduation rate). Second, high-performance and bottom-income students still have better results than low-performance and top-income students as in the previous outcomes (34% and 26% respectively).

In column (4), the probability sitting for the PSU upon graduation is explored. Again, there are two main findings. First, it can be seen that conditional on performance groups, the relation between income groups stay stable and consistent with the results from the baseline estimation. For instance, low performance students in both middle and top income-groups have a higher probability of taking the PSU than students in the bottom-income group (19% and 26% respectively). Second, high-performance, and bottom-income students still have better results than low-performance and top-income students as in the previous outcomes (34% and 26% respectively).

In column (5) and (6), the math and reading PSU scores are explored. As before, this estimation controls by potential selection bias. I discuss the following two findings. First, it can be seen that conditional on performance groups, the relation between income groups stay stable and consistent with the results from the baseline estimation. For instance, low-performance students in both middle and top-income groups have better results than students in the bottom income group (3.8 and 16.9 respectively in math scores, and similar in reading). Second, the evidence shows, consistently with the results until here, that high-performance students in the bottom-income group are above the low-performance in the high-income group (20.9 and 16.9 in the PSU math, respectively).

Finally, in column (7), the probability of obtaining a degree is explored. As the last output of the educational cycle, and from the evidence from the baseline estimations, we could expect those previous differences will remain. However, we can theorize that access to the different variety of institutions could diminish this problem if those institutions deliver satisfactory education to those students with less opportunities and worst previous outcomes. There are, in fact, institutions like the vocational education universities, who's focus is different from the skills usually evaluated by standardized test. Their aim is more related to endowing students with practical competences demanded by the labor market. I discuss the following two findings. First, conditional on performance groups, the relation between income groups stays stable and consistent with the results from the baseline estimation. For instance, low-performance students in both middle and top-income groups have better results than students in the bottom-income group (0.12 and 0.20 respectively). Second, consistently with the results until here, high-performance students in the bottom-income group have a higher probability of obtain a degree with respect to the low-performance in the high-income group (26% and 20%, respectively).

These results show little variation across the different stages of the educational cycle, and are rather consistent. On average, students from the top 10% of income have better

Table 3: Student Performance in the national distribution

	(1) SIMCE Math	(2) SIMCE Reading	(3) Finished High-School	(4) Took PSU	(5) PSU Math	(6) PSU Reading	(7) Degree
Bottom-Income & Medium Performance	9.31***	10.23***	0.14***	0.19***	6.31***	7.61***	0.14***
	(0.26)	(0.27)	(0.00)	(0.00)	(0.29)	(0.29)	(0.00)
Bottom-Income & High Performance	25.37***	24.24***	0.21***	0.34***	20.92***	20.95***	0.26***
	(0.30)	(0.29)	(0.00)	(0.00)	(0.32)	(0.32)	(0.00)
Middle-Income & Low Performance	4.21***	3.20***	0.13***	0.19***	3.76***	4.30***	0.12***
	(0.23)	(0.24)	(0.00)	(0.00)	(0.25)	(0.26)	(0.00)
Middle-Income & Medium Performance	16.09***	15.15***	0.22***	0.36***	14.39***	15.58***	0.28***
	(0.22)	(0.23)	(0.00)	(0.00)	(0.23)	(0.24)	(0.00)
Middle-Income & High Performance	33.56***	30.19***	0.26***	0.47***	31.89***	30.96***	0.40***
	(0.23)	(0.23)	(0.00)	(0.00)	(0.25)	(0.24)	(0.00)
Top-Income & Low Performance	14.50***	12.13***	0.12***	0.26***	16.87***	16.48***	0.20***
	(0.85)	(0.85)	(0.01)	(0.01)	(0.76)	(0.72)	(0.01)
Top-Income & Medium Performance	31.15***	26.14***	0.24***	0.48***	32.80***	30.92***	0.43***
	(0.40)	(0.41)	(0.00)	(0.00)	(0.41)	(0.39)	(0.01)
Top-Income & High Performance	47.23***	40.56***	0.27***	0.53***	49.58***	46.35***	0.53***
	(0.26)	(0.26)	(0.00)	(0.00)	(0.27)	(0.26)	(0.00)
N	223425	222656	223425	223425	201643	201818	223425

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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outcomes than the others students conditional on their income group. In addition, students from the bottom-income and high-performance group have on average better results than students from the top-income and low-performance group. These results show that family income matters, but if a child from the bottom-income group achieves a high performance relative to the national distribution, she can obtain better results than students from the 10% (with low performance). This last finding is relevant, but still leaves the question of just how low-income students can achieve a high performance at the national level and overcome, to some degree, the disadvantage posited by belonging to a lower income bracket.

5.2.2. Student Performance within the income group

This subsection analyzes the relation expressed in equation (3), except I now separate students by their relative performance within their income group. That is, within each income group, the students are separated in three groups based on their academic performance. Each group is equally sized within their income group. From above, the results show that students that are in the high-performance group and are from a bottom-income family have on average better results than students that are from a top-income family and had low-performance. However, the bottom-income students that achieves the high-performance group are scarce, in important part because of disparities that accumulate since birth (see Chetty and Hendren (2018) or Heckman et al. (2005)). Therefore, another reasonable question is how students perform conditional on being from a high-performance group within their income group. That is, how well a student from a low-income family that is one of the

best of her class performs with respect to a student from a high-income family that is also one of the best of her class (without considering if they are indeed in the high-performance group at the national level)? and how well does she perform with respect to a student from a high-income family that does not have a relatively bad performance in her class?

With the above definition, the estimation of equation (3) allows us to find a relative mobility measure conditional on relative student performance. Each income group has the same proportion of high, middle, and low performance students. As discussed above in an imperfect meritocratic world, the differences between groups conditional on performance should be relatively negligeable. An interesting metric to discuss is the difference between high performance and low performance students across the income distribution. We would expect that student with high-performance have better results than low-performance students both within and across income groups. That is, for instance, high performance students in the bottom-income group should have relatively better results that low performance students in the top-income group. It should be noted that by construction high-performance students in the bottom-income group could be part of the national middle or low-performance group defined in the above subsection.

In table 4 the main results are re-explored using these new groups. The counterfactual group is a student from the bottom income distribution and with low performance. Column (1) and (2) present the results for SIMCE math and reading tests. There are four findings to highlight. First, low-performance students from both middle and top-income groups have on average better SIMCE results than their classmates. Second, it is interesting to note that in the high-performance group, while students from the medium-income distribution are on average 35 percentiles above the poorest students, the ones from the top-income distribution tend to be 52 percentiles above the poorest. And lastly, high-performance students in the bottom of the income distribution have worst results than low-performance students in the top of the income distribution (21 and 28, respectively in the case of the math test)[8].

In table 4 the main results are re-explored using these new groups. The counterfactual group is student from the bottom income distribution and low performance. Column (1) and (2) present the results for SIMCE math and reading tests. There are four findings to highlight. First, it can be seen that low-performance students from both middle and top-income groups have on average better SIMCE results than their classmates from bottom-income group. Second, it is interesting to note that while high-performance students from the middle income distribution are on average 34.84 percentiles above than the poorest students, the ones from the top income distribution and high-performance tend to be 51.98 percentiles above the poorest. Third, high-performance students in the bottom of the income distribution have worst results than low-performance students in the top of the income distribution

[8]The difference between both coefficients is statistically significant.

(21.07 and 28.32 respectively in the case of the math test)[9].

In column (3) the probability of finishing high-school is explored. There are three findings to highlight. First, low-performance students from both medium and top-income groups have a higher probability of finishing than their counterparts from the bottom-income group (17 and 23 respectively). Second, it is observed that high-performance students in top-income group have a higher probability of finishing high-school than their low-income counterparts. And third, high-performance students in the bottom-income group have relatively worst results than low-performance students in the top-income group[10], similar to the findings in the previous columns.

In column (4), the probability of taking the PSU is explored. There are three findings to highlight. First, low-performance students in both middle and top-income groups have better results than bottom-income students (0.24 and 0.45 respectively). Second, higher-performance students in the top-income group have a considerably higher probability of taking the PSU than students of the same performance group but from the bottom income distribution (0.58 and 0.33 respectively). And third, high-performance students in the bottom-income group have a lower probability of taking the PSU than their counterparts in the top-income group (0.33 and 0.45 respectively).

In column (5) and (6), the correlation between income and performance and PSU scores is explored. As before, I control for potential sample bias in our estimations. There are three findings to highlight. First, low-performance students in both middle and top-income groups have better results than the ones in the bottom-income group (4 and 28 percentiles respectively in math, and similar in reading). Second, I also observe that higher-performance students in the top-income group have better results in PSU scores than bottom-income students of the same performance group (around 16 and 54 percentiles higher, respectively). And third, high-performance students in the bottom-income group have worst results in the PSU than their counterparts in the top-income group (around 4 and 28 percentiles higher, respectively).

In the column (7), the probability of obtaining a degree is explored. As discussed previously this is the last outcome, and is important because it marks the end of the educational cycle and is also highly correlated with future income. There are three findings to highlight. First, low-performance students in both middle and top-income groups have better results than bottom-income students (0.39 and 0.16 respectively). Second, I can also observe that higher-performance students in the top-income group have a higher probability of receiving a degree than bottom-income students of the same performance (around 0.58 and 0.25, respectively). And third, high-performance students in the bottom-income group have worse results than their counterparts in the top-income group (around 0.25 and 0.39, respectively).

[9]The difference between both coefficients is statistically significant.

[10]The difference between both coefficients is statistically significant.

Table 4: Students performance within Income Groups

	(1) SIMCE Math	(2) SIMCE Reading	(3) Finished High-School	(4) Took PSU	(5) PSU Math	(6) PSU Reading	(7) Degree
Bottom-Income & Medium Performance	5.30***	7.21***	0.12***	0.16***	1.79***	4.24***	0.11***
	(0.29)	(0.30)	(0.00)	(0.00)	(0.33)	(0.34)	(0.00)
Bottom-Income & High Performance	21.07***	21.42***	0.22***	0.33***	15.89***	17.25***	0.25***
	(0.28)	(0.29)	(0.00)	(0.00)	(0.32)	(0.33)	(0.00)
Middle-Income & Low Performance	5.97***	5.75***	0.17***	0.24***	4.23***	5.80***	0.16***
	(0.25)	(0.27)	(0.00)	(0.00)	(0.28)	(0.30)	(0.00)
Middle-Income & Medium Performance	18.37***	17.99***	0.26***	0.41***	15.41***	17.36***	0.31***
	(0.25)	(0.26)	(0.00)	(0.00)	(0.28)	(0.29)	(0.00)
Middle-Income & High Performance	34.84***	32.17***	0.29***	0.51***	32.07***	32.04***	0.42***
	(0.26)	(0.27)	(0.00)	(0.00)	(0.29)	(0.29)	(0.00)
Top-Income & Low Performance	28.32***	24.63***	0.23***	0.45***	28.57***	27.94***	0.39***
	(0.41)	(0.42)	(0.00)	(0.01)	(0.41)	(0.41)	(0.01)
Top-Income & Medium Performance	44.03***	37.92***	0.29***	0.56***	44.94***	42.60***	0.54***
	(0.32)	(0.34)	(0.00)	(0.00)	(0.35)	(0.35)	(0.01)
Top-Income & High Performance	51.98***	46.19***	0.30***	0.58***	53.47***	51.34***	0.58***
	(0.30)	(0.31)	(0.00)	(0.00)	(0.32)	(0.32)	(0.01)
N	223425	222656	223425	223425	201643	201818	223425

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[11]

These results show little variation across the different stages of the educational cycle, and are rather consistent. First, on average, and regardless of their performance group, students from the top-income group have better outcomes than students from the bottom-income group. This result is different from the one discussed in the previous subsection, where top-income students from the low-performance group had worst results than bottom-income and high-performance students. And second, from the above, the evidence presented suggests a stronger relation between the outcomes and income than our previous performance definition suggested. This is, using this definition, the income is a more stronger determinant of the future outcomes than using the definition from the previous section.

6. Geographical Results

In this section, the variation in intergenerational mobility across regions within Chile are presented. I start by defining the geographical units analyzed. Then, I present the results of mobility across the different regions, discussing the variations within the country.

6.1. Geographical Units

Chile is a diverse country across its different zones and regions. It is geographically characterized as a long narrow strip of land, that goes from the Andes mountains to the pacific ocean from east to west, and from the Atacama desert to the South Pole from north to

south (see figure 2 for a reference). In this long portion of land there are a distinct climates, subcultures and socioeconomic realities.

The country is divided from north to south in different macro-zones. In general, there are considered five macro-zones: North, Center, Center-South, South, and the Austral zone. The country is administratively divided in sixteen regions, from north to south. Almost all regions go from the Andes to the Pacific (except for the Metropolitan Region, that hosts the capital of the country, which is also landlocked). Each region is divided in *provinces*, and each province is divided in *municipalities* (or comunas).[12]. In general, a large city could have many municipalities within it. There is no city-level subdivision.

In this section section, I study differences at the regional level unit of analysis. This choice is deliberate for three main reasons. First, regional-level analysis exploits the relative homogeneity inside each region while also dealing with the potential spillovers that could exists between municipalities within a region. It is not common that people move across regions to study or work. Second, each region contains a significant number of students in the cohort that is being studied, so the estimations could be performed with a non-small number of observations. And third, the sixteen regions allow a reasonable number of comparisons across heterogeneous units. This analysis, however, does not incorporate potential heterogeneity within regions. In general, this does not pose a problems given that the regions evaluated are relatively internally homogeneous. However, the Metropolitan Region (where Santiago, the capital, is located), presents important differences across its different municipalities. In this sense, Santiago is a city that presents a significant geographical segregation (see for instance Otero et al., 2021, that discuss the segregation in Santiago). Future studies could be aimed at exploring these characteristics. As discussed above, a similar analysis could be performed using the municipality level of analysis

The table table 5 presents some descriptive statistics for each region in 2015[13]. It can be observed that there is considerable heterogeneity across these regions . For instance, the Metropolitan region is the biggest one, amassing around the 40% of the county´s total population. On the other end of the spectrum Aysen holds only 0.5% of the population. Also, the region with the highest average monthly income has around 2.5 times the income of the one with the lowest average. Thus, it is reasonable Ican expect our variables of mobility to

[12]Administratively, in Chile there are a few differences between both concepts. Comuna is the geographical unit and municipality refers to the administrative organism that manages the Comuna. There is one municipality per comuna, except for the municipality of Cabo de Hornos, which acts as administrator for both the comuna of the same name and the comuna of the Antartica. For simplicity in this work I use municipality as synonym for comuna.

[13]The income distribution differs from the one presented in the Family Income in 2002 because they are measures for different years (the incomes experimented an important growth in the 2000-2010 period) and different population (overall population in this table, and relatively young families with children around ten years). Considering that, seemed relevant to discuss an updated measure to characterize the regions.

vary significantly across the region.

Table 5: Regional Statistics (2015)

	Population	Pop. Fraction	Years of Schooling	Age	Monthly Income
North:					
Arica y Parinacota	167,793	0.96	36.2	10.81	919
Tarapacá	326,966	1.86	32.3	10.84	1,080
Antofagasta	574,413	3.27	33.8	11.20	1,373
Atacama	281,153	1.60	33.7	10.93	1,231
Center:					
Coquimbo	758,108	4.32	36.0	10.61	922
Valparaíso	1,824,098	10.39	37.8	10.96	933
Metropolitana	7,134,812	40.65	36.3	11.70	1,556
Center-South:					
O'Higgins	914,682	5.21	36.9	9.93	928
Maule	1,032,683	5.88	37.9	9.47	767
Ñuble	482,333	2.75	38.4	9.70	676
Bío-Bío	1,585,002	9.03	36.9	10.30	784
South:					
La Araucanía	983,653	5.60	37.3	9.52	686
Los Ríos	369,488	2.11	37.8	9.24	721
Los Lagos	863,439	4.92	37.0	9.32	818
Austral					
Aysén	103,207	0.59	35.1	10.11	1,129
Magallanes	150,675	0.86	38.7	10.65	1,234

Note: Own elaboration from CASEN 2015. The table shows the regional statistics for the sixteen regions of Chile in the year 2015. The regions are divided in five groups following a geographical criteria. The column Pop. Fraction contains the relative percentage of the regional population respect to the national population (around 13.35 millions). The column Years of Schooling shows the average of schooling year in the region. The column Age shows the average age of the population in the region. The column Monthly Income shows the average income in US$ dollars.

6.2. Relative and Absolute Mobility

To evaluate the mobility at the regional level, I draw a distinction between absolute and relative mobility. These two measures report different and complementary information with regards to the spirit of the intergenerational mobility characterization at the regional level. Then, I present the estimations at the regional level and discuss the relevant differences between the geographical units.

Relative mobility refers to the performance of students from low-income families relative to the performance of students from high-income families. As in the baseline estimations, the approach is to compare the performance of the students that belong to families that are in the top 10% of the income distribution relative to the performance of the students that belong to families that are in the bottom 30%. This measure indicates the differences between both groups. A higher correlation amongst the variables means that students from the top of the distribution are systematically excelling vis-as-vis those at the bottom, and,

in other words, that there is an absence of mobility. This definition implies that is possible to make comparisons between regions by running a similar regression to that used in the previous part. Then, it is possible to compare the coefficient related to the top income group with respect to the bottom income group.

Absolute mobility refers to the performance of students from low-income families in absolute terms. This measures indicate the absolute results of low-income students versus a baseline level of performance. A higher indicator in value is synonymous with better students from low-income families having better results, which is consistent with more mobility. Following Chetty et al. (2014), I use the performance of students whose parents are in the bottom 30% of the income distribution as a proxy[14].

6.2.1. Estimations of Relative Mobility

I start by examining the Relative Mobility measures at the regional level. I summarize the conditional expectation of a student outcome given her family' income in each region using a linear approximation (constant and slope). Let Y_{ir} denote an outcome of the student i that grew up in the region r. The list of outputs are the same as those outlined in the discussion about national level results, but keeping only the math test in the case of SIMCE and PSU tests.[15]. Let G_{ir}^{x} denotes a dummy variable that takes up the value of 1 if the family' income of student i from the region r belongs to the x group of income (top 10%, middle between 30% and 90% and bottom 30%). Taken together, I estimate the slope of the relationship in each specific region as follows:

$$Y_{ir} = \alpha_r + \beta_{1r} G_{ir}^{top} + \beta_{2r} G_{ir}^{middle} + \varepsilon_{ir} \tag{4}$$

Where β_{1r} measures the degree of relative mobility in each region r.

The estimates for coefficient β_{1r} in each region and output are presented in table 6.[16]. The regions are ordered from north to south, and are divided by macro-zones. All the coefficients are statistically significant across all regions and outputs. Column (1) shows the results for SIMCE math. The results range goes from just 23.6 percentiles of difference between the students in the top and the bottom-income groups in the Arica and Parinacota, in the North, to a difference of 40 percentiles in the metropolitan region, in the center and where the capital Santiago is located. As discussed above, higher coefficients mean that there is less relative

[14] Chetty et al. (2014) use the bottom 25%. Given that in the Chilean context the questionnaire where families report their incomes is expressed in income ranges, I am not able to distinguish those students from families in the bottom 25%. I use, then, the closest percentile available, which is the bottom 30%.

[15] Similar than in the baseline estimations, the results for reading in both test are consistent with respect to the math test, and are available upon request.

[16] An alternative geographical representation of the results can be found in part b of figure 2, figure 3, figure 4, figure 5 and figure 6

mobility, or in other words, that family' income matters more in terms of predict future student outcomes in that particular region. It is worth highlighting that the regions where the best results in terms of mobility can be seen are the regions of Arica and Parinacota ($\beta_1 = 23.6$) and Aysen ($\beta_1 = 29$). The other regions have less mobility and show similar results.

Column (2) shows the results related to the probability of finishing high-school. The range of differences in probability between top-income and bottom-income students goes from 10% in Arica and Parinacota to 25.5% in the Antofagasta region, both in the north. It is worth highlighting that the regions where the best results can be seen in terms of mobility are the regions of Los Rios ($\beta_1 = 0.11\%$), in the south, and Arica y Parinacota ($\beta_1 = 0.096\%$), in the North. As opposed to the previous case, the results are well distributed, and there are few regions with worst results. The higher coefficients (or lower mobility results) are in the regions of Antofagasta ($\beta_1 = 0.255\%$), in the north; Aysen ($\beta_1 = 0.244$), in the austral zone; and Atacama ($\beta_1 = 0.23$), also from the north. The case of Aysen stands out because it shows high mobility results in terms of the SIMCE, but low in terms of the probability of finishing high-school.

Column (3) shows the results related to the probability of taking PSU. The range of differences in probability between top-income and bottom-income students goes from a 30% in the Nuble region, in the south, to a difference of 52.1% in the Antofagasta region. It is worth highlighting that the regions where the higher results in terms of mobility can be seen are the regions of Nuble ($\beta_1 = 0.300$), in the center-south; Valparaiso ($\beta_1 = 0.304$), in the center; and Arica and Parinacota ($\beta_1 = 0.316$), in the North. On the other hand, the regions with the lower relative mobility are the regions of Antofagasta ($\beta_1 = 0.521$), in the north; and Magallanes ($\beta_1 = 0.481$) and Aysen ($\beta_1 = 0.470$), in the austral zone.

Column (4) shows the results relating to the PSU scores. These results control for the potential selection bias in the probability of taking the test. The differences in the percentiles of PSU scores between students in the top and the bottom of the income distribution go from 43 percentiles in the Metropolitan region, to 18 in Arica and Parinacota. It is worth highlighting that the northern region of Arica and Parinacota is by far the region with the highest mobility with a $\beta_1 = 18.9$. The second region is Magallanes ($\beta_1 = 27.9$) and Aysen ($\beta_1 = 29.7$), in the austral zone. On the other hand, the regions with less relative mobility are the Metropolitan ($\beta_1 = 43.06$) and Valparaiso ($\beta_1 = 39.47$) regions, in the center zone; and the Bio-Bio region, in the center-south zone ($\beta_1 = 39.15$)

Column (5) shows the results related to the probability of obtaining a degree from a higher-education institution. The difference in the probabilities of getting a degree between students in the top and bottom of the income distribution goes from 18.2% in Arica and Parinacota to 44.8% in the Metropolitan region. It is worth highlighting that the southern region of Los Rios is by far the region with the higher mobility with a $\beta_1 = 0.182$. The

next regions that exhibit high results are Maule ($\beta_1 = 0.278$) and Nuble ($\beta_1 = 0.283$), in the central-south zone. On the other hand, the regions with lower relative mobility are the Metropolitan ($\beta_1 = 0.448$) and Valparaiso ($\beta_1 = 0.394$) regions, in the center zone.

Table 6: Relative Mobility by Region

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
North:					
Arica y Parinacota	23.61***	0.0966***	0.316***	18.94***	0.182***
	(2.41)	(0.02)	(0.03)	(2.55)	(0.04)
Tarapacá	36.03***	0.213***	0.431***	33.52***	0.379***
	(1.95)	(0.02)	(0.02)	(2.01)	(0.03)
Antofagasta	38.13***	0.255***	0.521***	34.20***	0.356***
	(1.30)	(0.01)	(0.02)	(1.48)	(0.02)
Atacama	36.98***	0.230***	0.424***	36.09***	0.322***
	(1.89)	(0.02)	(0.02)	(1.81)	(0.03)
Center:					
Coquimbo	38.00***	0.139***	0.353***	38.22***	0.346***
	(1.20)	(0.01)	(0.01)	(1.24)	(0.02)
Valparaíso	37.92***	0.149***	0.304***	39.47***	0.394***
	(0.74)	(0.01)	(0.01)	(0.71)	(0.01)
Metropolitana	40.02***	0.188***	0.372***	43.06***	0.448***
	(0.34)	(0.00)	(0.00)	(0.34)	(0.01)
Center-South:					
O'Higgins	36.07***	0.160***	0.327***	38.61***	0.353***
	(1.14)	(0.01)	(0.01)	(1.08)	(0.02)
Maule	35.10***	0.148***	0.348***	36.41***	0.278***
	(1.15)	(0.01)	(0.01)	(1.10)	(0.02)
Ñuble	34.59***	0.126***	0.300***	35.15***	0.283***
	(1.81)	(0.02)	(0.02)	(1.76)	(0.03)
Bío-Bío	37.74***	0.157***	0.338***	39.15***	0.365***
	(0.77)	(0.01)	(0.01)	(0.73)	(0.01)
South:					
La Araucanía	35.44***	0.127***	0.359***	37.32***	0.342***
	(1.17)	(0.01)	(0.01)	(1.09)	(0.02)
Los Ríos	36.88***	0.110***	0.366***	37.42***	0.330***
	(1.73)	(0.02)	(0.02)	(1.77)	(0.03)
Los Lagos	37.01***	0.167***	0.453***	37.50***	0.375***
	(1.15)	(0.01)	(0.01)	(1.11)	(0.02)
Austral:					
Aysén	28.97***	0.244***	0.470***	29.73***	0.327***
	(2.82)	(0.03)	(0.03)	(2.88)	(0.04)
Magallanes	38.36***	0.160***	0.481***	27.88***	0.372***
	(2.44)	(0.02)	(0.03)	(2.95)	(0.03)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Each column reports the results of estimating the equation (4) using as dependent variable the specified variable at the top of the column. Each row shows the results for each region. Therefore, each cell shows the coefficient for relative mobility ($\hat{\beta_{1r}}$) associated to that region and dependent variable. Relative mobility measures the differences in outcome between the top 10% and the bottom 30% of the family' income distribution. Each region is grouped in five macro-zones in a geographical criteria. All standard error are robust.

The results for regions across the different outcomes through the educational cycle are relatively consistent. Overall, there are three general findings. First, The Metropolitan region systematically has the lowest results in terms of relative mobility when compared to other regions. This means that students that grew up there and belong to the bottom of the income distribution had the lower results relative to their counterparts on the top of the income distribution. This does not mean that the students from the bottom-income group in this region are in the region with less opportunities (this question is related to the concept of Absolute Mobility), but just that those students face significantly less opportunities than their counterparts in the top-income group (and that this difference is the widest in this region). The case of Santiago, the bigger city and capital of the country and the Metropolitan region, is interesting because of its well-known geographical segregation (Otero et al., 2021). This is, the degree in which students from certain groups of income are isolated from the rest. These results confirm that there are relevant differences in terms of opportunities between people in the bottom of the income distribution and the ones on the top. The specific characteristics that define the different opportunities and education access of students within the region are explored on the next section.

Second, other regions with systematic low relative mobility are Antofagasta (north) and Valparaiso (center). Antofagasta region depends importantly on the mining, and is a region that concentrate important earnings from that sector. However the mining rent usually does not stay in the region, the related wages are over the average of the country (see for instance, table 5 in the case of 2015). The other economic sectors in the region are less important, and in general the labor income in the region is low if the mining sector is excluded. In the other hand, Valparaiso region is very close to Santiago, and represent its closest sea access. The main cities in the region are Valparaiso and Vina del Mar. Both cities are close and form the metropolitan area of Valparaiso. They are, however, relatively different in socioeconomic terms. Vina del Mar has been historically comparatively richer than Valparaiso, that also hosts the main seaport. If because of the above, students from Vina del Mar are having on average better results than the ones from Valparaiso, and also Vina del Mar concentrates more students from the top-income distribution, could explain the low relative mobility in the region.

And third, on the opposite end of the spectrum, the region of Arica and Parinacota shows systematic good results throughout the educational cycle. Students from this region show the smaller differences between the bottom-income and top-income groups, or, equivalently, the students from the bottom-income group have the best relative chances to achieve good results. The differences with the other regions in the country are important for almost all variables, and particularly, they are very relevant in the probability of obtaining a degree. It is interesting to note, the large differences with respect to the regions of Tarapaca, Antofagasta -which ranks worst in terms of mobility - and Atacama, given that that are geograph-

ically very close to each other and share similar characteristics (see for instance, panel b in figure 2 or figure 6 that illustrate those differences.). What are the differences between these four regions that make Arica and Parinacota show such good results in comparison? And more in general, what are the differences between the regions with lower mobility and the ones with high mobility that determine these results? This question is crucial, and is explored in the following section analyzing potential of correlates of mobility.

6.2.2. Estimations of Absolute Mobility

In this subsection I discuss the results related to Absolute Mobility measures at the regional level. I define absolute mobility at percentile p in the region r as the expected outcome of a student who grew up in the region r and whose parents have an income lower than p% of the population. Recall that G_r^{top} takes the value of 1 if the student is from a family in the top 10% of the income distribution; G_r^{top} takes the value of 1 if the student is from a family in the group between the percentile 30% and 90% of the income distribution; and G_r^{bottom} takes the value of 1 if the student is from a family in the bottom 30% of the income distribution. Then, to calculate the expected outcome of the student from a family in a certain group of income and region I can use the equation above. That is, calculate the expected outcome for each region r and percentile p group as follows:

$$\begin{aligned} E[y_r|G_r^{top}=1] &= \hat{\alpha_r} + \hat{\beta}_{1r} \\ E[y_r|G_r^{middle}=1] &= \hat{\alpha_r} + \hat{\beta}_{2r} \\ E[y_r|G_r^{bottom}=1] &= \hat{\alpha_r} \end{aligned} \tag{5}$$

I focus the analysis on the average outcome for students from families with an income below the 30%, that is, $E[y_r|G_r^{bottom}=1] = \hat{\alpha_r}$. A higher average in the outcome is equivalent to a higher absolute mobility. This measure is comparable between regions.

The $\bar{y}_r$ for each region and output is in table 7.[17]. The regions are ordered from north to south, and are divided by macro-zone. Each row shows the average output for the people in the bottom 30% of the income distribution. The first column shows the results for SIMCE math. The range of the average percentile in the SIMCE math test for people in the bottom of the income distribution goes from percentile 43 in the Aysen region, in the Austral zone; to percentile 33 in Tarapaca, Antofagasta, both from the North, and Magallanaes, from the Austral zone. Other regions with good results in term of mobility are Arica and Parinacota, in the north, where students achieve on average the 41 percentile; Coquimbo (percentile 38), in the center; and Maule (percentile 39), in the center-south.

[17] An alternative geographical representation of the results can be found in part a of figure 2, figure 3, figure 4, figure 5 and figure 6

The second column shows the results related to the probability of finishing high-school. The average probability for students in the bottom 30% of the income distribution ranges from a 87% in Arica and Parinacota (as before) to 68% in Aysen. It is interesting to note that Aysen was the region where students in the bottom of the income distribution had better results in SIMCE math, but also, they were less likely to finish high-school. The other regions with the best results in term of mobility are Los Rios (82%) and La Araucania (80%), both from the south. The other cases with bad results in term of mobility are Antofagasta (70%) and Tarapaca (73%), both from the north.

The third column shows the results related to the probability of taking the PSU. The average probability for students in the bottom 30% of the income distribution range from a 62.7% in Valparaiso to 38.4% in Antofagasta. The other regions with the best results are Arica and Parinacota (59.9%), from the north; O'Higgins (57.2%), from the center-south; and the Metropolitan region (57%), from the center. The other cases with bad results are Antofagasta (38.4%), from the north; and Aysen (41.4%), from the south.

The fourth column shows the results related to the PSU scores. It is worth remembering that the coefficients used to calculate the conditional expectation of the scores percentile are corrected by the potential selection bias implicit in the decision of taking the test. The average percentile that students in the bottom 30% of the income distribution achieve goes from 42 in Magallanes to 34.8 in the Metropolitan region, in Coquimbo and in Valparaiso, all from the Center zone. It is interesting to observe, first, that all the regions that belong to the macro-zone Center have comparatively bad results; and second, that while the Metropolitan region and Valparaiso have relatively good results in the other variables, they perform poorly in terms of PSU scores. The other regions with the best results are Arica and Parinacota (percentile 41.5), in the north; and Aysen (percentile 41.4), in the south.

The last column shows the results related to the probability of obtaining a degree. The average probability for students in the bottom 30% of the income distribution range from a 31.1% in Nuble to 14.9% in Tarapaca. The other regions with the best results are Arica and Parinacota (28.6%), from the north; and Bio-Bio (28.2%), from the center-south. The other cases with bad results are Antofagasta (17.8%) and Atacama (19.3%), from the north; and the Metropolitan region (19.8%), from the center.

The Absolute mobility results are relatively consistent across regions and outputs through the educational cycle. They are also similar to the relative mobility results. This could be appreciate in figure 2 to figure 6. I highlight five relevant findings. First, absolute mobility varies substantially at the regional level. Antofagasta and Arica and Parinacota are good examples of regions that have different results in all the outcomes. In line with that, absolute mobility is not necessarily similar within macro-zones, though there are some shared patterns. For instance, the regions from the center zone are relatively homogeneous in their results. It is also possible to observe relevant patterns as well as important differences in the

Table 7: Absolute Mobility by Region

	SIMCE Math	Finished High-School	Took PSU	PSU Math	Degree
North:					
Arica y Parinacota	41.74	0.877	0.599	41.53	0.286
Tarapacá	32.54	0.728	0.470	35.03	0.149
Antofagasta	32.57	0.700	0.384	35.27	0.178
Atacama	35.33	0.723	0.474	35.99	0.193
Center:					
Coquimbo	38.03	0.818	0.559	34.80	0.221
Valparaíso	37.47	0.810	0.627	34.83	0.231
Metropolitana	37.62	0.781	0.570	34.78	0.198
Center-South:					
O'Higgins	37.88	0.790	0.572	35.76	0.257
Maule	39.41	0.779	0.535	39.36	0.259
Ñuble	39.56	0.811	0.569	37.82	0.311
Bío-Bío	38.70	0.784	0.569	37.63	0.282
South:					
La Araucanía	37.78	0.820	0.542	37.14	0.245
Los Ríos	37.35	0.830	0.515	36.52	0.228
Los Lagos	36.80	0.778	0.429	38.09	0.223
Austral:					
Aysén	43.48	0.685	0.414	40.04	0.210
Magallanes	32.76	0.806	0.428	41.97	0.241

Note: Each column reports the results of estimating the equation (4) using as dependent variable the specified variable at the top of the column. Each row shows the results for each region. Therefore, each cell shows the coefficient for absolute mobility (α_r) associated to that region and dependent variable. Absolute mobility measures the outcome of the bottom 30% of the family' income distribution. Each region is grouped in five macro-zones in a geographical criteria.

south zone.

Second, Antofagasta systematically shows worst results in terms of absolute mobility than other regions. This means that students that grew up there and belong to the bottom of the income distribution had the worst educational results in the country. It follows that on average, students from the bottom-income group that live in Antofagasta have less opportunities than students from any other region.

Third, the Metropolitan region, the most populous one, shows a relative bad performance. However, students from this region had good initial results, but then tend to perform worst in terms of PSU results and the probability of obtain a degree later in their education cycles. These findings match those of relative mobility. A child from the Metropolitan region that belongs to a family whose income is in the bottom of the distribution has less opportunities than his counterparts from families in the top of the income distribution; but also has, on average, less absolute opportunities. This could be seen as contradictory because Santiago metropolitan area, the most relevant urban area of the region (and of the country), is often seen as a land of opportunities where students from families with less resources can improve their socioeconomic outcomes. What is behind this phenomenon is there for an important question.

Fourth, Valparaiso is an example of a region with comparatively bad results in terms of relative mobility, but with significantly better results in terms of absolute mobility. That is, a student with low income from this region has worst results than his/her counterparts with high income, but not comparatively bad results when compared to students from low-income families nationally.

And fifth, the region of Arica and Parinacota shows systematic good results throughout the educational cycle. Students from this region have the best expected outcomes conditional on belonging to a family in the bottom 30% of the income distribution. This region also exhibits one of the best results in terms of relative mobility. Exploring why students in this region are having more opportunities in relation with students from other regions is crucial. In this sense, the difference with respect to Tarapaca, Antofagasta and Atacama, that tend to have comparatively bad results, is interesting. Regions with relative similar cultural and geographic characteristics, show significantly different levels of mobility.

7. Correlations of Intergenerational Mobility

In this section I explore the answer of why some regions in Chile exhibit higher mobility outcomes. As a first step toward answering it, I correlate the measures of intergenerational mobility with local characteristics. It is important to mention that such correlations should not be interpreted as causal relations. A relevant research agenda should aim to find the casual mechanisms to answer this question. In this document, however, my objective, in line

with Chetty et al. (2014), is to document a set of stylized facts implicit in the heterogeneity of results found in the case of Chile.

In this part, I correlate the mobility statistics discussed above with various factors that the literature considers relevant, such as segregation, inequality, and education quality. The results are focused on cross-sectional correlates rather than changes over time, given that the statistics of mobility are for one birth cohort. For the studied covariates, I use publicly available data. This includes the socioeconomic national household survey (CASEN), the SIMCE survey, and the educational ministry public reports.

Furthermore, for the purpose of this section, I use an even smaller geographical unit. Now the mobility measures in section 6 are re-calculated at the municipality level. The heterogeneity on the results at the regional level are robust at the municipality level, being consistent in magnitude and relation. See, for instance, figure 8, that presents the measures of absolute mobility in the case of the Probability of obtain a higher-education degree. As the colors are darkest, the municipalities present higher mobility measures; while the lighters colors reflect municipalities with low mobility (relative to other municipalities). I redefine the geographical unit in the spirit of obtaining a higher variation in the mobility measures, and with that, be better able to exploit the variations in the correlates. In this sense, the country has 345 municipalities in total, which allows us to perform a better analysis than in the previous case of 16 regions. It is worth to mention that a potential problem of this perspective is potential spatial correlation between municipalities. If students are able to move between them, eventually the characteristics of the municipalities in the neighborhood could be also relevant to explain the mobility at the local level. However, as the big cities where students can move between municipalities present in general a high degree of segregation, eventually the characteristics of the municipalities should not change dramatically across borders.

From the 345 municipalities, I include only the ones with more than 75 students in the relevant cohort. There are 265 municipalities that satisfy the condition of minimum students. The average number of students in the remaining municipalities is 279. Then, in the next subsections I analyze the absolute mobility measure given by the average outcome at the municipality level, conditional on belong to a family in the bottom 30% of the distribution ($E[y_c|G_c^{bottom}] = \alpha_C$). As discussed previously, a higher outcome implies that students from low-income families obtain better results, and thus there is a greater degree of mobility.

7.1. Segregation

There is literature on how segregation serves as a determinant factor on the availability of social opportunities and mobility (Otero et al. (2021), Chetty et al. (2014), and Cutler and Glaeser (1997)). The channels though segregation operates are, among others, (i) the reduc-

tion in students exposure to successful peers and role models, (ii) the potential scarcity of resources available in the segregated groups, and (iii) the implicit barriers to access good job opportunities. I explore this relation by analyzing the correlation between intergenerational mobility in terms of education and school segregation. If school segregation impacts the differences in terms of mobility, then the correlation should be statistically significant.

Following Chetty et al. (2014), I measure income segregation using a Theil (1972) index. Let's denote σ_g as the fraction of students in the income group g in a given region, with four income groups. The standard top 10% and bottom 30% used until here and separating the previous middle-income group in to two different groups: income between 30% and 66% and income between the 66% and 90% of the national distribution. I add the additional groups to distinguish between the high-middle income and the low-middle income groups. Lets, then, define the entropy index E as a measure of income diversity in the municipality, such that:

$$E = \sum \phi_g log_2 \frac{1}{\phi_g}$$

With $\phi_g log_2 \frac{1}{\phi_g} = 0$ when $\phi_g = 0$.

Lets now define $s = 1, ..., N$ as an index that indicates school s, and consider that each school is located in a municipality c. Analogously, I measure income diversity within each school as $E_s = \sum \phi_{gs} log_2 \frac{1}{\phi_{gs}}$, where ϕ_{gs} denotes the fraction of individuals of group of income g in school s. Finally, let n and n_s stand for the number of students in the municipality c and the number of students in the school s. Therefore, I define the degree of income segregation in the region as:

$$H = \sum_s \left[\frac{n_s}{n} \frac{E - E_s}{E} \right]$$

In this context, H measures the extent to which the income distribution in each school deviates from the overall income distribution in the municipality. The segregation index H is maximized at $H = 1$, when there is no income heterogeneity within schools, in which case $E_s = 0$ in all schools. It is minimized at $H = 0$, when all schools have an income composition identical to the municipality as a whole, so $E_s = E$. It should be noted that this definition considers segregation as any concentration of a specific group. Then, for instance, in a municipality with high-income and a lack of diversity, the index is probably closer to one as opposed to zero.

Having calculated the segregation index H for each municipality, it is possible to estimate its correlation with the mobility measures as follows:

$$y_c = \alpha + \beta H_c + \varepsilon_c \tag{6}$$

The OLS estimations of equation (6) for the different outcomes are presented in table 8. It is possible to observe that the coefficient β is not statistically significant in the case of the SIMCE math scores, the probability of finishing high-school, the probability of taking the PSU and the PSU math scores. The only case where the coefficient is significant is in the estimation of the probability of obtaining a degree. Recall that obtaining (or not) a degree is the last output in the educational cycle and can be thought of as a consequence of all the previous stages. Also, it has strong implications in the future of the student, particularly with regards to the opportunities that they face in the labor market and her future professional trajectory. In column (5) I show that the correlation between income segregation and mobility, expressed as the probability of obtaining a degree, is -0.189. That is, municipalities where there is a higher degree of segregation, students show, on average, a lower probability of obtaining a degree. This result is consistent with the findings in Chetty et al. (2014) and Sharkey and Graham (2013).

Table 8: Segregation

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Segregation Index	-5.391	0.0247	0.0281	5.307	-0.0296
	(4.283)	(0.0540)	(0.0618)	(3.436)	(0.0545)
Observations	311	312	312	310	312

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column reports coefficients from an OLS regression with robust standard errors. The regressions are run using data for all the municipalities with at least 75 students in the sample. The dependent variable is the expected outcome conditional on belong to a family whose income is in the bottom 30% of the distribution. Income segregation is measured using a Theil index.

From the definition of segregation that used here, I draw no distinctions between specific types of segregation. For instance, a municipality with high segregation could have a concentration of students from the top income group or from the bottom one. But do all types of segregation have the same effect on mobility? To answer this, I break down the effects of segregation into two types. Following Reardon and Bischoff (2011), I define two types of segregation: segregation of poverty and segregation of affluence. Segregation of poverty refers to the extent to which individuals in the bottom of the distribution are segregated from those above in the income distribution. Segregation of affluence refers to the extent to which individuals in the top of the distribution are segregated from those below in the income distribution. Consistently with the previous analysis, I define the bottom income group as the students that are below the 30% of the distribution. Similarly, students in the top income group are the ones on the top 10% of the distribution.

In table 9, I present the results of the OLS regression of the different outcomes on segregation of poverty and affluence. The probability of taking the PSU is negatively correlated

with the segregation of poverty. Municipalities where students from the bottom of the family income distribution are segregated tend to have a lower probability of taking the PSU. This could be explained by a potential non-positive "peer effect" from their classmates. That is, some students who are not considering taking the PSU but see that their peers also do not want to take it, they end up not giving the test. A similar explanation could be that schools with high levels of segregation do not push their students to take the test.

The probability of obtaining a degree is, as opposed to the above, correlated with the segregation of affluence. Students from municipalities where their counterparts from the top income group are more concentrated have, on average, a lower probability of obtaining a degree. A potential explanation is that the concentration of the students in the top income group implies that the potential peer effects that could boost the possibilities for students in the bottom of the income distribution are absent. Also, it could be related to lower economic resources available for non-top-income students. It is interesting to note that this relevant finding is associated with isolation of high-income families (rather than the isolation of the poor), which suggests that it may be most detrimental for low income student's opportunities when the rich students are isolated.

The findings on probability of taking the PSU are consistent with the results that Chetty et al. (2014) found in the case of the United States, where they noticed that the isolation of low-income families is the type of segregation that can be most detrimental for low-income students.

Table 9: Segregation of poverty and affluence

	(1)	(2)	(3)	(4)	(5)
	SIMCE Math	Finished High-School	Took PSU	PSU Math	Degree
Segregation of Poverty H(p=33)	-6.452	0.0120	-0.0227	2.197	0.00440
	(3.368)	(0.0413)	(0.0497)	(2.891)	(0.0440)
Segregation of Affluence H(p=90)	0.833	0.0221	0.0345	2.448	-0.0323
	(1.826)	(0.0167)	(0.0243)	(1.490)	(0.0188)
Observations	311	312	312	310	312

Standard errors in parentheses

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Notes: Each column reports coefficients from an OLS regression with robust standard errors. The regressions are performed using data for all the municipalities with at least 75 students in the sample. The dependent variable is the expected outcome conditional on belong to a family whose income is in the bottom 30% of the distribution. Income segregation is measured using a Theil index.

7.2. Income Distribution

In this subsection I explore the correlation between mobility and income distribution, both in terms of level and inequality.

7.2.1. Median Income Levels

I begin analyzing the correlation between income levels and mobility. Eventually students in low-income families could obtain different results if they grow up in high-income municipalities.

Using data from the Chilean socioeconomic characterization survey (CASEN), I calculate the median income[18] for each municipality with a population greater than 500 inhabitants. There are 233 municipalities with valid observations for both mobility and income. Then, defining I as the natural logarithm of the median income, I estimate the following equation:

$$y_c = \alpha + \beta I_c + \varepsilon_c \tag{7}$$

The OLS regression results are presented in table 10. Column (1) to (4) show that there is no significant relation between income and mobility, expressed as SIMCE scores, the probability of finishing high-school, and the probability of taking the PSU. Column (5), however, shows that there is negative correlation between median income and the probability that a student from a low-income family obtains a degree. An extra 1% of median income is related with an increase of 6% in the probability of obtaining a degree. This result is different with respect to that reported in Chetty et al. (2014), where no effect was found. The difference between both results could be explained by the results in the segregation subsection. While in Chile the segregation of affluence is negatively correlated with mobility (measured as the probability of obtaining a degree among students in low-income families), Chetty et al. (2014) did not find a significant correlation in the United States. Thus, the implicit segregation of affluence in high-income municipalities, could be behind the difference in the findings in both works. Another possible explanation could be that, indeed, in Chile students from low-income families face discrimination (or other type of barriers to access) in high-income municipalities, which makes it less likely to obtain a degree. A third possible explanation is that in high-income municipalities the quality of public education is wanting because most of the students attend private schools. This is unlikely, given the relatively good results public schools in high-income municipalities usually obtain in standardized tests as well as other in other educational outcomes.

7.2.2. Inequality

Another interesting relation is between income inequality and mobility. So far, I have discussed the correlation between mobility and segregation and income levels, but is inequality also related with mobility? Recent work has found evidence of a a negative correlation between income inequality and intergenerational mobility across countries (Chetty et al. (2014); Corak (2013)). If true, this suggests that greater inequality within a generation

[18] The results are consist using both median and mean.

Table 10: Income and Mobility

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Median Income	0.350	-0.0173	0.0205	-0.406	-0.0627***
	(1.301)	(0.0113)	(0.0162)	(1.108)	(0.0111)
Observations	233	233	233	233	233

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column reports coefficients from an OLS regression with robust standard errors. The median income is included in log terms. The median income is calculated for each municipality with valid data.

could reduce the social mobility in a society. I explore an analogous question across municipalities within Chile. Then, defining $Ineq_c$ as a measure for inequality in the municipality c, the relation between inequality and mobility is given by β in the following equation:

$$y_c = \alpha + \beta Ineq_c + \varepsilon_c \tag{8}$$

I start analyzing the correlation between mobility and the Gini coefficient, calculated using CASEN data. As a precautionary note, it is worth pointing out that I use a local Gini coefficient that is constructed with survey data. There is an important research discussion surrounding how useful it is to calculate income inequality using survey data, although the general consensus is that inequality tends to be underestimated using this type of sources (see for instance, Flores et al., 2020, in the Chilean case). However, for the purposes of this work, it is still useful to use this definition and picture a raw correlation between the mentioned variables. Then, using the family income distribution, I compute the Gini coefficient for each municipality ($Gini_c$) with more than 500 families.

The OLS results for each outcome are reported in Panel A in table 11. I find no correlation between inequality, measured as the Gini index, and any of the outputs for students in low-income families.

Considering the potential problems of the Gini coefficient calculated with the available data, I perform the same estimation using two alternative measures of inequality. In the context of the rise in inequality in the last years driven primarily by an increase in top income shares (Piketty and Saez (2003)), I focus the attention on the share of income that those on the top receive in relation to the other percentiles of income.

First, I construct the ratio 90/10 in each municipality. That is, the ratio between the aggregated income of the top 10% of the distribution and the one of the bottom 10%. This measure captures the differences between the top income families and the bottom income families. The results when incorporated it proxies for inequality are presented in Panel B in table 11. As in the previous case, the correlation with each one of the mobility outcomes is

not statistically significant.

Second, I construct the ratio 90/50 in each municipality. That is, the ratio between the aggregated income of the top 10% of the distribution and the one from bottom 50%. This indicator, as oppose to the ratio 90/10 ratio, measures how much the top 10% captures in relation to the share of the 50%. Doing so, it incorporates not only the low-income families, but also a part of the middle class. The results of incorporating it as the inequality measure are presented in Panel C in table 11. As in the previous case, the correlation with each one of the mobility outcomes is not statistically significant.

Table 11: Inequality and Mobility

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel A:					
Gini Index	4.594	-0.0188	-0.0157	3.400	-0.0822
	(6.255)	(0.0679)	(0.105)	(5.069)	(0.0731)
Observations	233	233	233	233	233
	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel B:					
Ratio 90/10	0.335	0.000644	0.00340	0.351*	-0.00139
	(0.184)	(0.00219)	(0.00293)	(0.155)	(0.00253)
Observations	233	233	233	233	233
	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel C:					
Ratio 90/50	0.763	0.00318	0.00245	0.950	-0.00418
	(0.558)	(0.00820)	(0.00828)	(0.500)	(0.00962)
Observations	233	233	233	233	233

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column reports coefficients from an OLS regression with robust standard errors. The three inequality indicators are constructed using the socioeconomic characterization survey (CASEN). The municipalities incorporated are the ones with valid mobility results and with a number of families superior to 500.

The results presented in this subsection are different from the ones in Chetty et al. (2014), in the United States, or Corak (2013), when considering a cross country comparison. While I find no evidence of a significant relation, they indeed find a negative correlation between income inequality and mobility. In the first work the strong association is found when using a Gini coefficient. However, when the share of the top 1% is used, a much weaker relation is found.

7.3. School Quality

In this subsection I discuss the correlation between the mobility measures and various proxies for school quality. The intuition behind this is that higher quality schools could im-

prove student outcomes, and thus, mobility. To construct the proxies of school quality I use information from the Education Ministry and SIMCE and PSU test results. Then, defining SQ_c as the average school quality on municipality c, I estimate the following equation:

$$y_c = \alpha + \beta SQ_c + \varepsilon_c \tag{9}$$

7.3.1. Average School Outcomes

To begin, I use as proxy of school quality the average of SIMCE math scores. Thus, I calculate the average of school quality in each municipality; this is, the average of the average in each school. For comparability I standardize the average, so the results could be read as an improvement in one standard deviation in test scores. One standard deviation is equivalent to 53 points in the SIMCE scores. Using this measure, I analyze the correlate between the mobility measures and school quality. Panel A in table 12 presents the OLS results. I observe that the average school quality in the municipality is strongly correlated with almost all the outcomes. In general, municipalities with better schools have better mobility results. One extra standard deviation is related to an increase of the average SIMCE percentile by 7.8, the probability of taking the PSU by 7.7%, and the average PSU percentile by 5.2. The probability of finishing graduating school and obtaining a degree are not statistically significant.

Panel B shows the results for the regression including as variable the average performance of public schools in the municipality. It should be considered that all municipalities have at least two public schools and that there are on average 13 public schools per municipality (while there are an average of 24 schools regardless the school dependence). I discuss three main findings. First, as before, almost all outputs are strongly correlated with the average score of the public schools. Moreover, almost all correlations are higher than in Panel A (with the only exception of the probability of take the PSU). This evidence suggests that more than the overall average of school quality in the municipality, the variable that have the strongest relation with mobility is the quality of public schools. Second, both, the probability of finishing high-school and of obtain a degree are now statistically significant. One extra standard deviation in the average scores in the municipality is related with an increase of 7.4% and 8.4% of the probability of finishing high-school and the probability of obtain a degree, respectively. This could mean that the relation with the scores of the other type of schools might be, in fact, negative. I explore this implication in Panel C. And third, While the other variables are now significant, the correlation with the probability of take the PSU is now not statistically significant. This change of significance could be related, as before, with higher results derived from the other type of schools. It also means that students in good public schools do not change significantly their decisions of whether to take or not the PSU.

Panel C shows the estimation now including the scores for voucher and private schools. This estimation presents an additional selection problem: not all municipalities have these

types of schools. Thus, it is necessary to correct for the decision of opening a voucher or private school in a specific municipality. I apply a Heckman correction using as selection variables the average income of the municipality, the number of public schools and the number of students in the municipality. The results in panel C are from the second stage of the Heckman equation. There is one observation less because a single municipality did not have a valid observation for income.

Table 12: School Quality: Average School Tests

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel A:					
Average School Simce	7.8305***	0.0211	0.0771***	5.2104***	0.0225
	(1.4283)	(0.0158)	(0.0231)	(1.2522)	(0.0180)
Observations	233	233	233	233	233
	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel B:					
Public Schools Simce	11.2627***	0.0641***	0.0174	9.5436***	0.0890***
	(1.7801)	(0.0201)	(0.0336)	(1.6064)	(0.0186)
Observations	233	233	233	233	233
	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel C:					
Public Schools Simce	16.2846***	0.1349***	0.0094	14.7382***	0.0761***
	(2.8766)	(0.0314)	(0.0567)	(2.0917)	(0.0266)
Voucher Schools Simce	-1.3647	-0.0127	0.0173	2.7206	0.0153
	(2.1984)	(0.0264)	(0.0377)	(1.6670)	(0.0200)
Private Schools Simce	-0.3288	-0.0218	-0.0076	0.1689	0.0011
	(1.3000)	(0.0251)	(0.0375)	(1.1891)	(0.0182)
N	232	232	232	232	232

Standard errors in parentheses

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

Notes: Each column reports coefficients from an OLS regression with robust standard errors.

There are three main findings to discuss. First, the coefficients for quality of public schools are in general bigger than in Panel B, and, thus, in Panel A (the probability of taking the PSU is not significant and the coefficient related to degree is relatively lower than in the previous case). Second, the coefficients for quality of voucher and private schools are not significant for all variables. This implies that the performance of low-income students is strongly related to public schools, and not to the performance of private or voucher schools. It is to be expected that quality of private schools has no relation with the outcomes of low-income students, who rarely study there. It is, however, more relevant that quality of

voucher schools has no significant correlation (in fact, the sign is not even positive). There are two main hypotheses as to why the correlation could be positive: a direct and an indirect effect. The direct effect is given by the low-income students that indeed study in these type of schools. As discussed in the Chilean System section, low-income students could access sometimes to voucher schools through scholarships or to very low copay schools. The indirect effect is given by positive spillovers from the competition between schools as discussed by some authors in the literature (see for instance Correa et al., 2014). The results in Panel C in table 12 partially contradicts those two hypothesis, and is also partially aligned with the literature that find no relevant positive effect as results of the competition (Hsieh and Urquiola (2006), Contreras et al. (2010)).

7.3.2. Class Size

In this subsection I use as proxy of quality the average class size in the municipality, following Chetty et al. (2014) or Betts (1995). But class size effects might have a strong non-linearity component. Thus, I add the squared class size as covariate in equation (9).

Panel A in table 13 shows the results of the estimation. I find a quadratic relation between class size and some mobility outcomes. The correlation is significant (both, the linear and quadratic coefficients) with SIMCE math scores, the probability of taking the PSU and of obtaining a degree. The relation is concave, but quickly turns negative. That is, while in the beginning more students are positive in terms of the average results, the relation starts skewing negative, and more students are in fact worst in terms of mobility. The maximum in a quadratic relation $y = \alpha + \beta_1 n + \beta_2 n^2$ is given by $n = -\beta_1/\beta_2$. Therefore, in Panel A, the maximum results are achieved with an average class size of 21, 24 and 23 in the case of column (1), (3) and (5). Above those class sizes, students begin to obtain worst results. In other words, low-income students obtain better results in smaller classes (until certain point); and thus, the mobility is negatively related with class size. This result is consistent with the one reported in Chetty et al. (2014).

Panel B shows the result of estimating the same specification as above but using the public-school average class size. The correlations are weaker in this case, and only the coefficient related to the probability of obtain a degree remains significant. In this case, the general results from above still hold, but turn negative at an even smaller class size. In other words, the relation is concave, turning to negative at around 17 students. This finding implies that eventually the class size relation is important from a systemic perspective, and not only in the public sector.

This argument is reinforced in panel C, where the relation dissipates, and there are only weak coefficients. The only interesting finding is that the public school class size squared coefficient is significant at the 10%, implying that the relation is negative across the entire class size distribution.

Table 13: School Quality: Class Size

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel A:					
Class Size	1.0973***	0.0021	0.0145***	0.4502	0.0128***
	(0.3778)	(0.0038)	(0.0056)	(0.3124)	(0.0037)
Class Size Squared	-0.0255***	-0.0001	-0.0003**	-0.0123*	-0.0003***
	(0.0083)	(0.0001)	(0.0001)	(0.0070)	(0.0001)
Observations	233	233	233	233	233

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel B:					
Class Size: Public	0.3277	0.0008	0.0095	0.0009	0.0098**
	(0.3986)	(0.0042)	(0.0060)	(0.3399)	(0.0038)
Class Size: Public (sq.)	-0.0073	-0.0000	-0.0002	-0.0016	-0.0003***
	(0.0085)	(0.0001)	(0.0001)	(0.0073)	(0.0001)
Observations	233	233	233	233	233

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel C:					
Class Size: Public	-0.5379	-0.0077	0.0196	-1.0448	0.0115
	(0.8890)	(0.0098)	(0.0182)	(0.8275)	(0.0086)
Class Size: Public (sq.)	0.0092	0.0001	-0.0003	0.0165	-0.0003*
	(0.0167)	(0.0002)	(0.0003)	(0.0155)	(0.0002)
Class Size: Voucher	0.3145	-0.0117	0.0004	0.0351	-0.0047
	(0.7839)	(0.0178)	(0.0171)	(0.8462)	(0.0057)
Class Size: Voucher (sq.)	-0.0107	0.0001	-0.0000	-0.0033	0.0001
	(0.0130)	(0.0003)	(0.0003)	(0.0145)	(0.0001)
Class Size: Private	-0.7628*	-0.0040	-0.0010	-0.1710	-0.0006
	(0.3956)	(0.0041)	(0.0077)	(0.4195)	(0.0033)
Class Size: Private (sq.)	0.0211*	0.0001	-0.0000	0.0074	0.0000
	(0.0110)	(0.0001)	(0.0002)	(0.0115)	(0.0001)
N	232	232	232	232	232

Standard errors in parentheses

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

Notes: Each column reports coefficients from an OLS regression with robust standard errors. Class size: Public and Class size: Public (sq.) are variables that contains the average class size and its squared version. Similarly for the voucher and private versions.

8. Conclusion & Further Research

This paper presents a characterization of the Intergenerational Mobility in terms of educational outcomes in Chile. Students from high-income families have better average outcomes than those from low-income families. This is also true when comparing students with similar initial levels of performance. Moreover, there are significant spatial variation across regions. For instance, the probability that a low-income student obtains a university degree is 31.1% in Nuble and just 14.9% in Tarapaca. The spatial variation is strongly correlated with public schools' quality levels. However, these results should not be interpreted as causal effects, but only as correlations. If this last result corresponds to a causal relation, investments in education and policy geared towards improving school quality could lead to improved mobility.

The analysis presented does not include labor outputs that could complement this study to give an even fuller characterization of mobility in Chile. Also, we do not differentiate our results in terms of type of higher-education degree (be it CFT, Professional Institute or University) or the quality of the institution where the students is graduating from (as in Cellini and Turner (2019) or Hastings et al. (2013)). Future research could deepen the analysis incorporating this nuance. Another potential research agenda could attempt to arrive at causal explanations for the heterogeneity of mobility at the local level. This could include both, re-exploring the performance outcomes discussed her or include new potential correlates.

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S. E. Black and P. J. Devereux. Chapter 16 - recent developments in intergenerational mobility**we would like to thank anders björklund, dan hamermesh, helena holmlund, kanikakapur, gary solon, alexandra spitz-oener, and steve trejo for helpful comments. prudence kwenda provided excellent research assistance. devereux thanks the irish research council for the humanities and social sciences (irchss) for financial support. this chapter was completed while black was on leave from the economics department at ucla. e-mail addresses: sblack@austin.utexas.edu (sandra e. black), devereux@ucd.ie (paul j. devereux). volume 4 of *Handbook of Labor Economics*, pages 1487–1541. Elsevier, 2011. doi: https://doi.org/10.1016/S0169-7218(11)02414-2. URL `https://www.sciencedirect.com/science/article/pii/S0169721811024142`. 2

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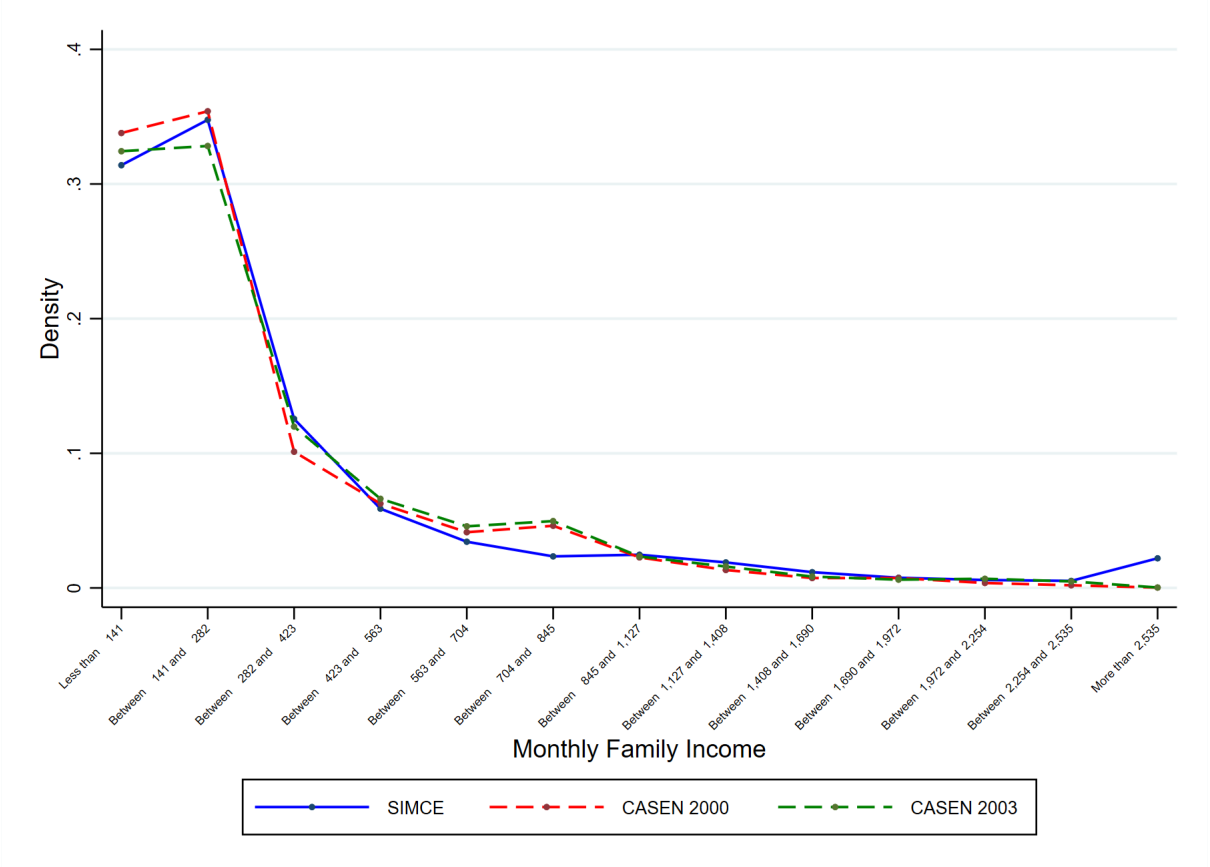
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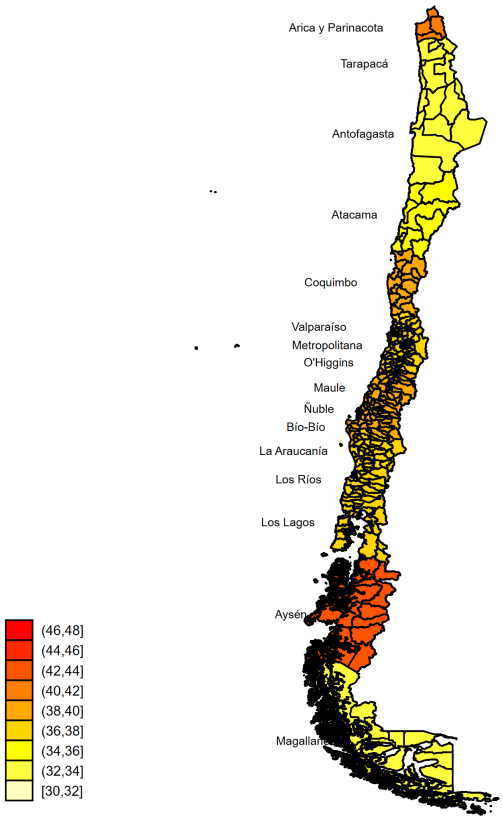
Figure 1: Income Distribution in SIMCE and CASEN



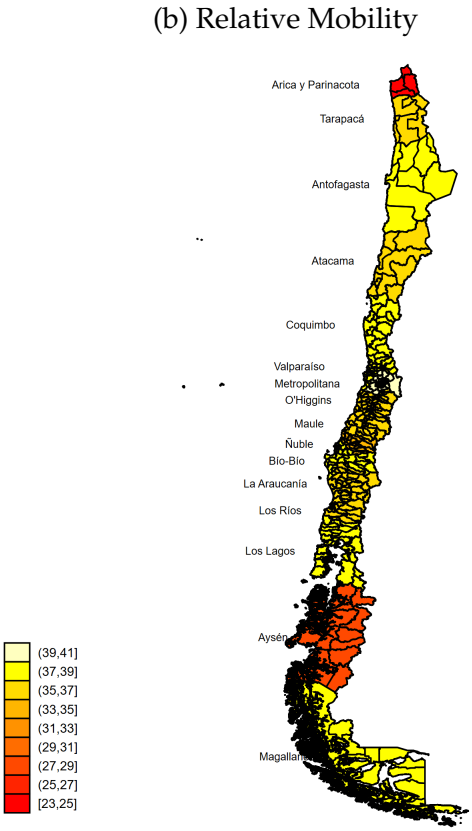
Note: The graph shows the income distribution from the CASEN 2003 and 2006 surveys and the SIMCE 2002 parent questionnaire. In CASEN, the income is calculated for those families with a children close to ten years, to make it the sample comparables.

Figure 2: SIMCE Math results at Regional Level

(a) Absolute Mobility



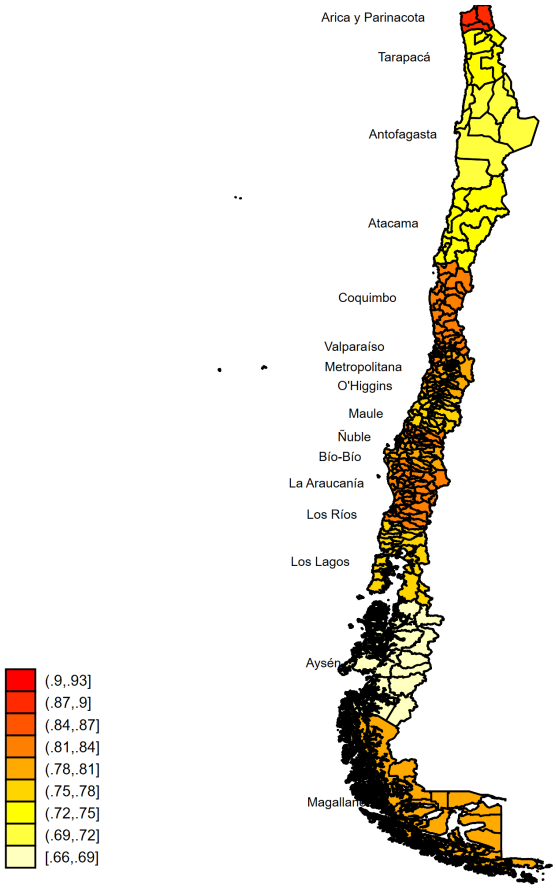
(b) Relative Mobility



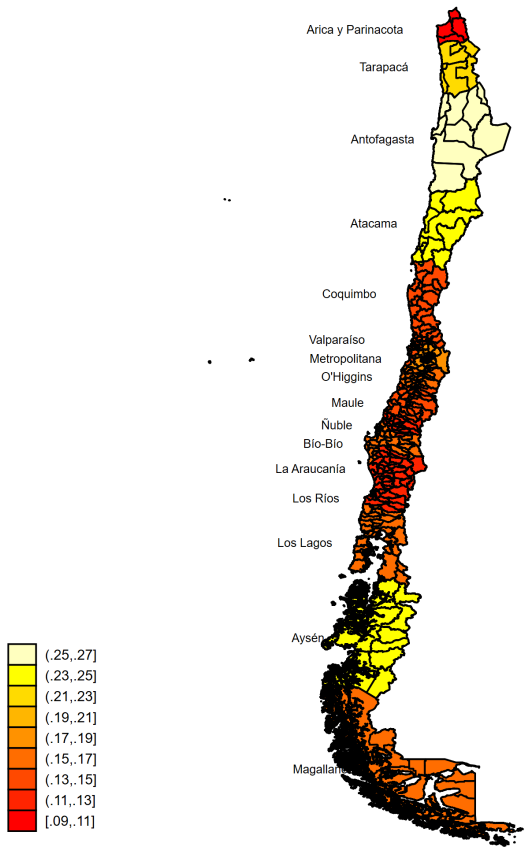
Note: The figures show the absolute and relative mobility measures for the SIMCE Math results at the regional level. The redder, the greater the mobility. The clearer, the lower the mobility. The absolute mobility measures the average outcome of students in the bottom 30% of the income distribution. Thus, a higher average, implies a higher mobility, and is expressed as redder in the map. The relative mobility measures the average outcome of a student in the top 10% of the income distribution in relation to the bottom 30%. Thus, a higher average, implies a lower mobility, and is expressed as clearer in the map.

Figure 3: Probability of Finish Secondary at Regional Level

(a) Absolute Mobility



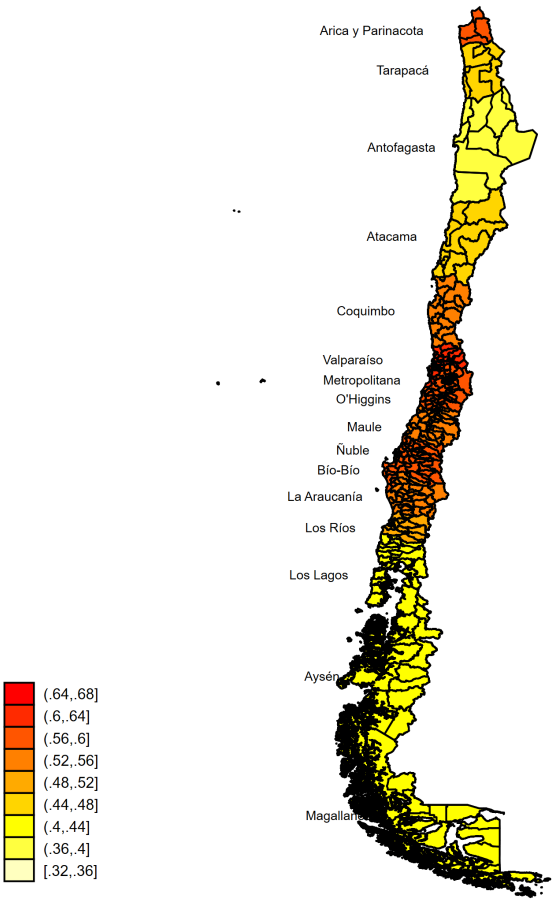
(b) Relative Mobility



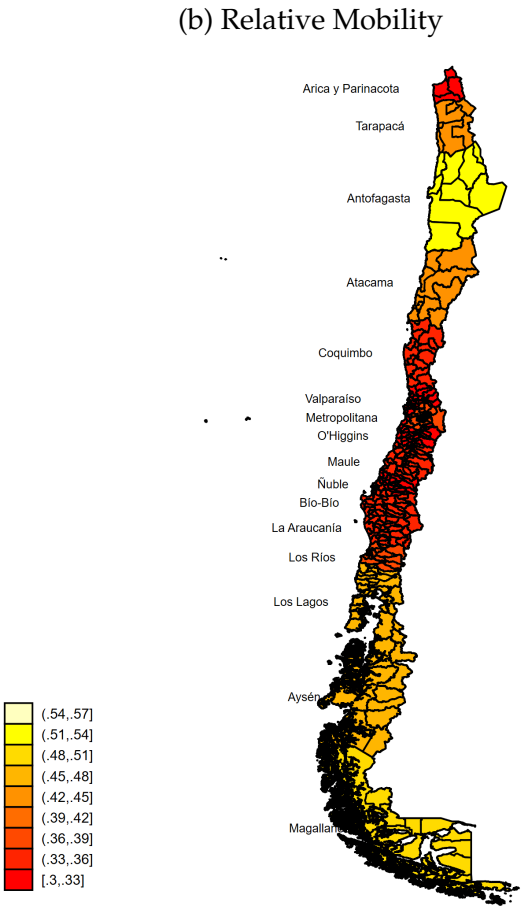
Note: The figures show the absolute and relative mobility measures for the Probability of finish secondary education at the regional level. The redder, the greater the mobility. The clearer, the lower the mobility. The absolute mobility measures the average outcome of students in the bottom 30% of the income distribution. Thus, a higher average, implies a higher mobility, and is expressed as redder in the map. The relative mobility measures the average outcome of a student in the top 10% of the income distribution in relation to the bottom 30%. Thus, a higher average, implies a lower mobility, and is expressed as clearer in the map.

Figure 4: Probability of Take the PSU at Regional Level

(a) Absolute Mobility

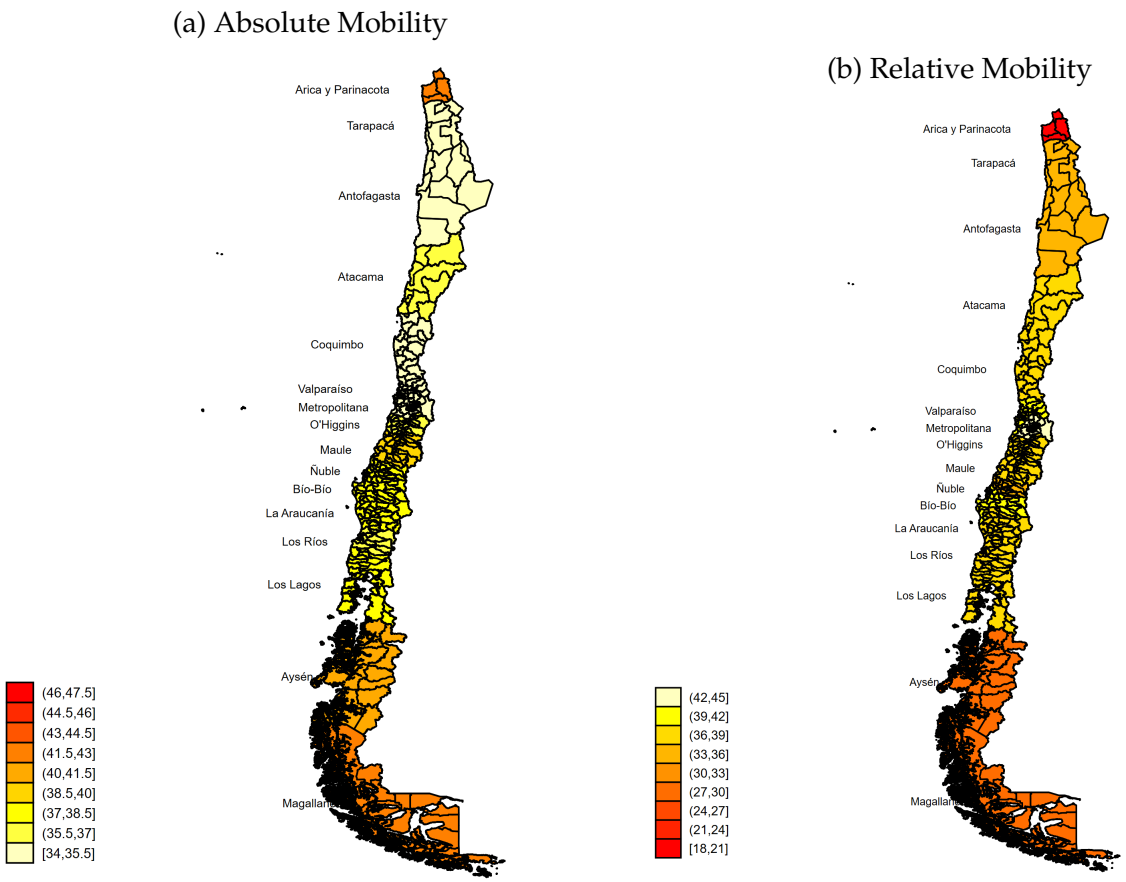


(b) Relative Mobility



Note: The figures show the absolute and relative mobility measures for the Probability of take the PSU at the regional level. The redder, the greater the mobility. The clearer, the lower the mobility. The absolute mobility measures the average outcome of students in the bottom 30% of the income distribution. Thus, a higher average, implies a higher mobility, and is expressed as redder in the map. The relative mobility measures the average outcome of a student in the top 10% of the income distribution in relation to the bottom 30%. Thus, a higher average, implies a lower mobility, and is expressed as clearer in the map.

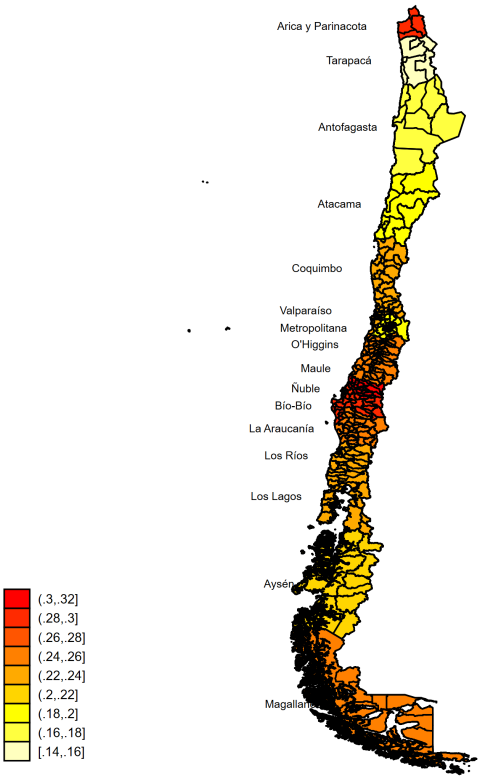
Figure 5: PSU Math Results at Regional Level



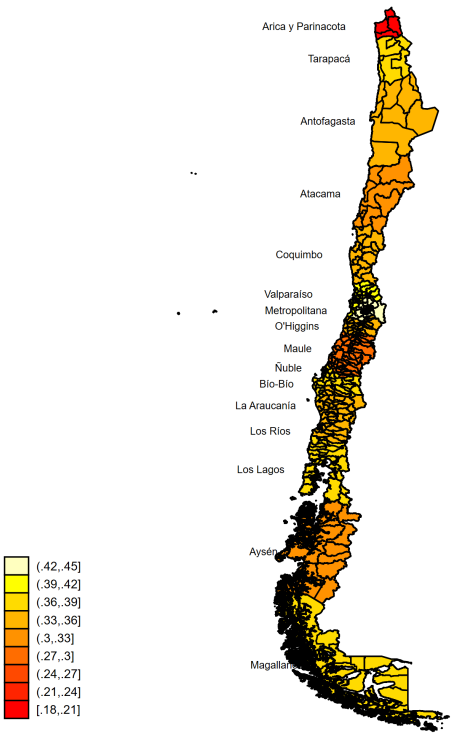
Note: The figures show the absolute and relative mobility measures for the PSU math results at the regional level. The redder, the greater the mobility. The clearer, the lower the mobility. The absolute mobility measures the average outcome of students in the bottom 30% of the income distribution. Thus, a higher average, implies a higher mobility, and is expressed as redder in the map. The relative mobility measures the average outcome of a student in the top 10% of the income distribution in relation to the bottom 30%. Thus, a higher average, implies a lower mobility, and is expressed as clearer in the map.

Figure 6: Absolute Mobility & Prob. Obtain a Higher-Education degree at Regional Level

(a) Absolute Mobility

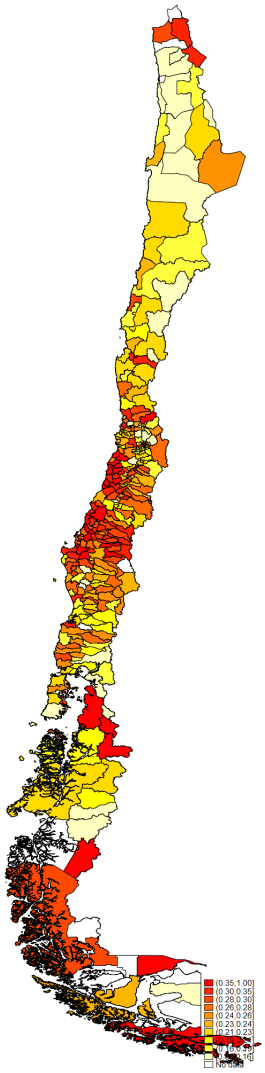


(b) Relative Mobility



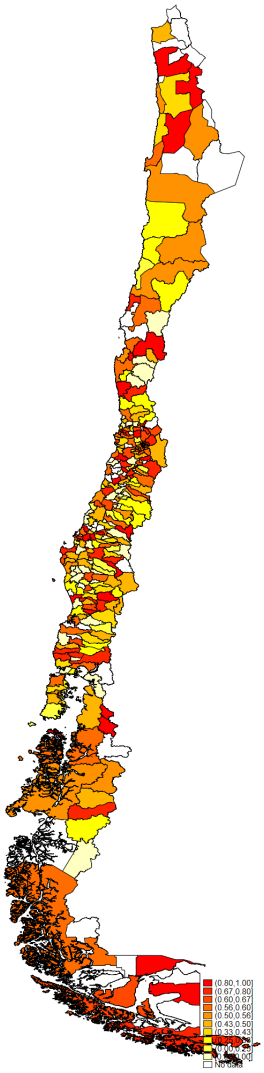
Note: The figures show the absolute and relative mobility measures for the Probability of obtain a degree in a higher-education institution at the regional level. The redder, the greater the mobility. The clearer, the lower the mobility. The absolute mobility measures the average outcome of students in the bottom 30% of the income distribution. Thus, a higher average, implies a higher mobility, and is expressed as redder in the map. The relative mobility measures the average outcome of a student in the top 10% of the income distribution in relation to the bottom 30%. Thus, a higher average, implies a lower mobility, and is expressed as clearer in the map.

Figure 7: Prob. Obtain a Higher-Education degree at Municipality Level



Note: The figure shows the absolute mobility measure for the Probability of obtain a degree in a higher-education institution at the municipal level. The redder, the greater the mobility. The clearer, the lower the mobility. The absolute mobility measures the average outcome of students in the bottom 30% of the income distribution. Thus, a higher average, implies a higher mobility, and is expressed as redder in the map.

Figure 8: Relative Mobility & Prob. Obtain a Higher-Education degree at Municipality Level



Note: The figure shows the absolute mobility measure for the Probability of obtain a degree in a higher-education institution at the municipal level. The redder, the greater the mobility. The clearer, the lower the mobility. The absolute mobility measures the average outcome of students in the bottom 30% of the income distribution. Thus, a higher average, implies a higher mobility, and is expressed as redder in the map.

Appendix

Table 14: Segregation & Relative Mobility

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Segregation Index	24.77**	0.0158	-0.0225	20.96**	-0.120
	(7.674)	(0.0764)	(0.0818)	(7.472)	(0.101)
Observations	283	283	283	282	283

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column reports coefficients from an OLS regression with robust standard errors. The regressions are run using data for all the municipalities with at least 75 students in the sample. The dependent variable is the expected outcome conditional on belong to a family whose income is in the bottom 30% of the distribution. Income segregation is measured using a Theil index.

Table 15: Segregation & Relative Mobility

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Segregation of Poverty H(p=33)	-16.01**	-0.163**	-0.304***	-16.02**	-0.325***
	(4.828)	(0.0512)	(0.0580)	(4.866)	(0.0616)
Segregation of Affluence H(p=90)	24.29***	0.0742	0.123*	23.58***	0.0778
	(4.148)	(0.0401)	(0.0506)	(4.155)	(0.0535)
Observations	283	283	283	282	283

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column reports coefficients from an OLS regression with robust standard errors. The regressions are performed using data for all the municipalities with at least 75 students in the sample. The dependent variable is the expected outcome conditional on belong to a family whose income is in the bottom 30% of the distribution. Income segregation is measured using a Theil index.

Table 16: Relative Mobility & Income

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Median Income	0.350	-0.0173	0.0205	-0.406	-0.0627***
	(1.301)	(0.0113)	(0.0162)	(1.108)	(0.0111)
Observations	233	233	233	233	233

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column reports coefficients from an OLS regression with robust standard errors. The median income is included in log terms. The median income is calculated for each municipality with valid data.

Table 17: Relative Mobility & Inequality

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel A:					
Gini Index	85.84***	0.275*	0.308	82.92***	0.584*
	(18.82)	(0.139)	(0.213)	(17.40)	(0.257)
Observations	233	233	233	233	233
	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel B:					
Ratio 90/10	3.176***	0.0107*	0.0226***	2.991***	0.0309***
	(0.670)	(0.00421)	(0.00637)	(0.598)	(0.00652)
Observations	233	233	233	233	233
	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel C:					
Ratio 90/50	9.568***	0.0294*	0.0599**	10.09***	0.0948***
	(2.460)	(0.0138)	(0.0207)	(2.452)	(0.0243)
Observations	233	233	233	233	233

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Each column reports coefficients from an OLS regression with robust standard errors. The three inequality indicators are constructed using the socioeconomic characterization survey (CASEN). The municipalities incorporated are the ones with valid mobility results and with a number of families superior to 500.

Table 18: Relative Mobility & School Quality: Average School Tests

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel A:					
Average School Simce	32.3291***	0.1471***	0.2790***	30.5372***	0.3110***
	(4.8409)	(0.0429)	(0.0569)	(4.7254)	(0.0594)
Observations	220	220	220	220	220
	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel B:					
Public Schools Simce	10.2056	0.0083	0.0621	12.7963*	0.0952
	(7.5190)	(0.0540)	(0.0734)	(6.8877)	(0.0831)
Observations	220	220	220	220	220
	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel C:					
Public Schools Simce	-7.1315	-0.0563	-0.0484	10.4223***	0.0505
	(9.6862)	(0.0522)	(0.0574)	(4.0355)	(0.0531)
Voucher Schools Simce	15.4513	0.0786	0.0773	-3.6737	0.0042
	(10.2813)	(0.0729)	(0.0578)	(4.0207)	(0.0462)
Private Schools Simce	13.4838***	0.0337	0.0397	9.5118***	0.0787*
	(4.5931)	(0.0249)	(0.0257)	(3.2738)	(0.0445)
N	219	219	219	219	219

Standard errors in parentheses

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

Notes: Each column reports coefficients from an OLS regression with robust standard errors.

Table 19: Relative Mobility & School Quality: Class Size

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel A:					
Class Size	2.8237*	0.0126	0.0257	1.9840	0.0589***
	(1.6548)	(0.0134)	(0.0179)	(1.5081)	(0.0184)
Class Size Squared	-0.0401	-0.0001	-0.0003	-0.0280	-0.0011***
	(0.0350)	(0.0003)	(0.0004)	(0.0323)	(0.0004)
Observations	220	220	220	220	220

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel B:					
Class Size: Public	1.2129	-0.0094	0.0034	0.5352	0.0210
	(1.4317)	(0.0111)	(0.0160)	(1.3877)	(0.0179)
Class Size: Public (sq.)	-0.0044	0.0003	0.0002	0.0060	-0.0003
	(0.0293)	(0.0002)	(0.0003)	(0.0290)	(0.0004)
Observations	220	220	220	220	220

	(1) SIMCE Math	(2) Finished High-School	(3) Took PSU	(4) PSU Math	(5) Degree
Panel C:					
Class Size: Public	-1.3070	-0.0044	-0.0059	-0.5174	-0.0406
	(1.7665)	(0.0122)	(0.0135)	(1.4260)	(0.0286)
Class Size: Public (sq.)	0.0186	0.0001	0.0001	0.0092	0.0008
	(0.0315)	(0.0002)	(0.0002)	(0.0259)	(0.0005)
Class Size: Voucher	2.4635	0.0275*	0.0239*	-2.4209	0.0118
	(2.4487)	(0.0152)	(0.0144)	(2.0507)	(0.0156)
Class Size: Voucher (sq.)	-0.0408	-0.0005*	-0.0004*	0.0351	-0.0003
	(0.0384)	(0.0002)	(0.0002)	(0.0332)	(0.0003)
Class Size: Private	3.4663**	0.0113	0.0134	1.5608*	0.0130
	(1.4597)	(0.0090)	(0.0088)	(0.8645)	(0.0120)
Class Size: Private (sq.)	-0.0878**	-0.0003	-0.0003	-0.0382	-0.0003
	(0.0399)	(0.0002)	(0.0002)	(0.0237)	(0.0003)
N	219	219	219	219	219

Standard errors in parentheses

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

Notes: Each column reports coefficients from an OLS regression with robust standard errors. Class size: Public and Class size: Public (sq.) are variables that contains the average class size and its squared version. Similarly for the voucher and private versions.