Intergenerational Mobility in Chile: A year-to-year analysis of a national cohort of students

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What are the factors that affect social mobility? How are early adulthood educational and labor trajectories correlated with intergenerational mobility? This paper presents three contributions to the intergenerational mobility literature. First, this paper develops one of the first attempts to measure intergenerational mobility using administrative panel data sets in a developing country. A panel data was created using a national educational test and surveys and follows students, starting in 8th grade, and analyzes their intergenerational income mobility at 27 years of age. Second, this paper uses social class and role models proxies and shows that the college educational outcomes are related to initial social and educational environments. Third, a detailed analysis of academic and labor market trajectories is used, indicating that students with irregular educational and labor market trajectories show lower intergenerational income mobility. The results of this research open a new approach for analyzing life decisions and expects to provide further guidance for public policies that intend to promote social mobility among low-income individuals.

I. Introduction

The question of intergenerational mobility has risen in importance in public debate over the several past decades. Intergenerational mobility can be defined as the extent to which an individual's background influences his or her adult income (Becker and Tomes, 1979). In an un-equal democratic country, intergenerational mobility is a critical counterweight that allows market economies and democratic systems to coexist (Corak, 2013). Therefore, factors that increase intergenerational mobility have gained public policy importance in a world with rising inequality. However the research on intergenerational mobility is constrained in different developing countries that lack panel data sets (Krishna and Nolan, 2019), and by the constraints of merging tax data with other information sources in developed countries.

The empirical research on intergenerational mobility has evolved into two significant branches, helped by the availability of detailed administrative information

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(Iversen et al., 2019; Palomino et al., 2018). The first branch of the literature focuses on how to measure intergenerational mobility, what data to use, and how to expand the measurements in different countries. [1].

The second branch of the literature is focused on understanding the factors that promote intergenerational mobility, and how these components affect different individuals. This branch of the literature centers on the dynamics that affect intergenerational mobility, the factors that promote it, the roadblocks that prevent it, and the policies that affect it. Current research has shown that intergenerational mobility is affected by different elements or channels that include family environment (ethnicity, family characteristics, neighborhood), education (early education, school education, college education) and health (prenatal health, birth characteristics, nutrition, life time health) (Chetty et al., 2014; Heckman, 2006; Streib, 2011; Torche, 2011, 2015). The educational literature has shown that role models and life shocks affect educational attainment (Altmejd et al., 2020; Torche, 2010) and therefore these variables should be incorporated into the analysis to evaluate their impact on intergenerational mobility.

The traditional methodology used to estimate intergenerational income mobility compares the long-term incomes of parents and their children. This methodology evaluates parents and children at a particular point in time. However, while some of the factors or channels that affect intergenerational mobility are fixed during life (genetics), others change over time (health or education) and depend on a plethora of factors and decisions. These current approaches to measuring the factors that affect intergenerational mobility do not consider the outcomes of adult children in terms of trajectory, where initial decisions affect subsequent ones. For example, educational investments build upon each other, and initial investments in during early education or high-school will increase the likelihood of achieving a college education (Chetty et al., 2011).

Therefore, analysis that does not differentiate between the timing of decisions could be distorting estimates of the factors that affect social mobility, as sometimes it is not possible to see which decisions were made first. Moreover, some connections are lost as it is not possible to analyze the interaction of choices at different moments in time. Furthermore, it could be possible that family characteristics and educational or work decisions at one particular moment in time may have a sizable effect, while the impact of the same choices later in life may be less decisive or inpactful. Following the adult children over a period of years via a yearly panel data set could be useful in documenting critical decisions that affect their intergenerational mobility and could shed some light on the importance of decision dynamics and family characteristics at different moments in their life time.

This paper is one of the first papers to use administrative data to measure

[1] This element of the literature is useful as it explains the macro trends at the country level, brings up the topic of intergenerational mobility, and informs the public. The deployment of various sources of information has produced diverse methodologies for analyzing the information and estimating social mobility, further contributing to the academic debate.

intergenerational mobility in a developing country. Moreover, it contributes to the literature by using year-to-year control variables, taking advantage of the vast and detailed administrative information including survey data on the educational system in Chile. Using administrative data, this paper creates a panel data set by following one full cohort of students, starting in 8th grade, through education and labor market in Chile. The panel includes data from two national mandatory educational tests, a voluntary test, and wages of students in adulthood. This data also includes information on the educational trajectories for all students and the early labor market outcomes for over 72% of the sample. It also provides detailed information on other potential factors including educational performance.

The results show that students in the lowest income quartile in 8th grade have a 9% probability of rising to the top income decile. However, these students could face many difficulties in economic mobility as they have low college enrollment and graduation rates. This paper analyzes the correlation between educational outcomes and intergenerational mobility, using as controls academic tests, and proxies of social class and role models. These results find that social class and and school environments are correlated with higher ranking positions, and indicate that previous research, which does not consider school environments and social class, could be overestimating the importance of academic outcomes on intergenerational mobility. In addition, the use of educational and labor market trajectories shows that different educational trajectories, which could seem similar looking as educational outcomes, are correlated with different intergenerational income mobility results. Individuals with irregular educational and work trajectories - gap years in education or unemployment periods - present lower intergenerational mobility.

II. Background Literature

The literature on intergenerational mobility has been re-invigorated during recent decades, as it has become a topic of public debate and policy, introducing new causal techniques and administrative data sets. One branch of the literature has focused on measuring intergenerational mobility; while a second branch focuses on analyzing its causes, estimating the effect of education, neighborhoods, nutrition, health, and labor markets on it during different parts of the lifecycle[2].

When measuring intergenerational mobility, transition matrices are one of the most basic tools. This methodology separates the adult children and parents into groups and analyzing if and how adult children move from their parents' group to another. Transition matrices are useful as they are not affected by changes in variance of the outcome variable, allowing for the comparison of results without having to standardize the data. [3] Using administrative data sets, another approach was developed by Dahl and DeLeire (2008) and later Chetty et al.

[2]This second branch is nurtured by the methodological developments of the first, taking advantage of the empirical innovations and data set developments

[3]Intergenerational Elasticity (IGE) is the standard measurement in the economic literature used to

(2014). Chetty et al. (2014), using tax records in the United States, ranks parents according to their income and ranks children according to theirs. Then a rank-rank regression is performed, where the rank-rank coefficient is the outcome of interest and is not affected by changes in the variance or level of income[4].

A. Education

When analyzing intergenerational mobility, education is one of the variables that has been proven, on both theoretical and empirical grounds, to promote it. Both causal and correlational empirical studies have concluded that education has a strong effect on intergenerational mobility (Chetty et al., 2011; Pekkarinen et al., 2009; Torche, 2011). There is an extensive array of literature that analyses educational investments, measuring the effect that they have on social mobility in developed and developing countries. As human capital investments are endogenous to family characteristics, different scholars have used various strategies to identify the causal effect of education on intergenerational mobility (Björklund and Jäntti, 2009). Various aspects of parental education transmit advantages to children (higher income, time allocation to family, and maternal education redistributes income to children). At the pre-school level, Chetty et al. (2011) analyze the effect of Project Star, a randomized policy in the USA, finding that better educational environments (smaller class sizes, experienced teachers, and classmates with higher test scoress) are associated with positive labor market outcomes and college attendance.

National policy interventions have been a useful way to measure the effect of primary and secondary education on intergenerational mobility, as they can be evaluated as natural experiments. For example, increases in mandatory education or enrollment capacity have improved educational and intergenerational mobility, proving this causal relationship (Maurin and McNally, 2008; Oreopoulos et al., 2006; Perkins, 1965). Moreover, formal education may not be the only factor that increases labor market outcomes, but also the acquisition of soft skills such as self-efficacy and self-esteem (Krishna, 2013).

relate parental income with child's income, and is usually estimated over the logs of income (log-log). However, the IGE has estimation problems as income variance changes over different cohorts. The differences in the income variance of the child's cohort will affect the estimations, making them not bounded between 0 and 1.

[4]The lack of intergenerational surveys in some countries has motivated the development of new methodologies using cross-section surveys, retrospective questions, or synthetic connections. However, retrospective questions are problematic, as children have a difficult time recalling their parents' income (Chetty et al., 2014). Another approach is proposed by Björklund and Jäntti (1997), using parental education and occupation as an instrument to predict income. This methodology consists of estimating an earning equation using parental cohorts. Then these estimated coefficients are used to predict parental income in the sample of children who reported retrospective parental information. Using the predicted parental wages, then IGE can be calculated. This methodology is known as the two-sample two-stage least squares (TSTSLS) or two-sample instrumental variable (TSIV) (Nunez and Miranda, 2010). This methodology and subsequent variations of "synthetic fathers" has allowed for the expansion of the literature in developing countries that did not have the money, time or institutional capacity to perform longitudinal surveys, but have the capacity to perform cross-sectional ones (Narayan et al., 2018; OECD, 2018)

There are a battery of studies that have analyzed the positive effects of higher education on intergenerational mobility. The reduction of restrictions for college education after the 1968 student movement in France promoted social mobility (Maurin and McNally, 2008). Using national surveys, Palomino et al. (2018) and Torche (2011) analyze the effect of higher education on social mobility in the US, confirming a positive correlation, but also recognizing the different effects that it has for students from different income groups. College affirmative action programs have a positive impact on increasing the educational attainment of students by enrolling them in programs that can lead to higher expected wages (Bagde et al., 2016; Gallegos et al., 2019). To quantify the role of higher education institutions, Chetty et al. (2017) estimate the effect of colleges on social mobility, finding positive effects. However, although groundbreaking in the use of new administrative data, as noted by the authors, their estimations are not causal. This is related to the fact that college education is a choice at the end of the educational pipeline, which obscures previous educational choices that could bias their estimations. Other variables, such as prior education, academic performance, role models, and others may affect the decision to attend college. Therefore, there is still space to further explore the relative importance of these initial variables on intergenerational mobility[5].

The economic literature on intergenerational mobility has made great efforts to analyze the correlation of ethnicity, geographical areas, college education or educational tracks on intergenerational mobility. However, other factors such as social class and educational environments -usually analyzed by the sociological and educational literature- have lack the same level of attention. The omission of these factors is relevant as students' educational decision are usually affected by their social origin and educational environment. Social reproduction theory stresses that social backgrounds and conditions determine educational attainments (Bourdieu, 1986). Social hierarchies harm educational mobility (Jacoby and Mansuri, 2015), but also performance in simple ability and effort tasks once hierarchies are made known (Hoff and Pandey, 2004). Students from higher social classes have more strategies and tools to succeed in college, compared to lower-class students, generating unequal outcomes (Yee, 2016). Social class has been identified as a factor affecting children's behaviors as early as four years old Streib (2011); it also impacts the behavior of students in classrooms and teachers (Rist,

[5]While there is consensus that on average higher education promotes social mobility, it is also true that for some groups of students, this is not always the case. In some countries, higher education could be reinforcing inequality (Haveman and Smeeding, 2006). The expansion of higher education in Britain disproportionately benefited higher income groups, increasing inequality (Machin, 2007). Using a sociological approach, and following more than 50 students over six years, Armstrong and Hamilton (2013) find that college education tends to maintain initial inequalities. For India, Iversen et al. (2019) note that there is a disconnect between educational mobility and occupational mobility as other characteristics (gender, identity, or location) may be making it harder to transform educational gains into labor market ones . Bucarey et al. (2018) find that students who enrolled in college in Chile and were at the margin of the financial aid cutoff do not obtain higher wages when compared to their counterparts who did not enroll in college. These authors attribute this effect to low-quality institutions and under-prepared students who do not graduate from college

1970), students' perspectives about future work (Hoxby and Turner, 2015), the choice of universities (Hoxby and Avery, 2012), and access to high paying jobs (Marmaros and Sacerdote, 2002; Ashley et al., 2015; Rivera, 2011, 2016). Experimental and non-experimental research on role models (Mani and Riley, 2019; Nguyen, 2008), information (Hastings et al., 2015; Hoxby and Turner, 2013), and aspirations have been able to show the important educational consequences of these decisions (i.e. dropping out of high-school or pursuing a low-profitable degree), particularly for low-income students (Zirkel, 2002). These studies show that decisions, social class, and role models at different points in life affect individuals' lifetime outcomes.

In summary, the literature overall has found a causal link between education, from early education to college, and social mobility worldwide. However, these educational decisions are also affected by individuals' social origins. Additionally, the literature uses point-to-point analyses without an analysis of student trajectories. As noted by the same authors, the reviewed papers did not address trajectories, but only the outcomes of two points in time, and it could be the case that when the decisions are made, and how they are made, affect intergenerational mobility.

B. Other Factors

While this paper focuses on the educational channels that promote intergenerational mobility, there are other important factors that affect it as well such as geography, neighborhoods, maternal nutrition, children's health, infrastructure investments, labor markets, etc. Some of these factors may be of particular importance in the developing world given the bigger geographical and health divides. There has been a re-enforcement of the importance of the analysis of geography and neighborhoods in the literature in developed countries. Previous research demonstrated the importance of family factors in intergenerational mobility over other factors such as neighborhood (Björklund and Jäntti 2009). In the developing world, there is an important rural-urban divide of opportunities (Iversen et al., 2019).[6] These differences are, in fact, very relevant for the developing world and should not be overlooked. Recent research studies have strengthened the theory that neighborhoods of residence are a relevant factor impacting social mobility in the developed world (Ananat et al., 2011; Chetty et al., 2014). New research that supports this argument uses randomized residential voucher programs in the US that demonstrate the importance of living in better neighborhoods (Bergman et al., 2019; Chetty, Hendren, and Katz 2016). These authors have obtained data on child and parental income, commuting zones, and other characteristics, but lack important data of inter-neighborhood factors s, like educational trajectories and other neighborhood-related services that are not controlled for. This paper

[6]In the developing world, it's possible that the low availability of services or state capacity in rural areas may affecte intergeneratinoal mobility

will try to include details in the educational trajectories and deepen the analysis beyond geographical location, to be able to provide guidance to policymakers. Although this paper tries to create a comprehensive understanding of educational trajectories, certain factors from other areas are not included. For example this paper does not include variables such as student health or early nutrition as there is little information available on these types of topics for this panel data set.

C. Brief Background on Chile

While there is a fast growing field of research on intergenerational mobility in developed and developing countries such as India, China, and Brazil, the research is much less developed for Chile (for a review see Behrman (2019); Iversen et al. (2019); Torche (2019)). The analysis of intergenerational mobility in Chile is nascent, with only a few studies dedicated to the topic. Torche (2005)) analyzed occupational mobility in Chile, finding that there is fluidity except for richer groups, which have low downward mobility. Using synthetic parents methodology and the 2006 CASEN survey, Nunez and Miranda (2010) estimate intergenerational income mobility in Chile, finding a high IGE estimate of over .54. This indicates that there is a low intergenerational income mobility in Chile compared to the developed world (0.12 for Denmark, 0.35 for USA, and 0.47 for France (OECD, 2018)). This low intergenerational income mobility is somewhat correlated with education. Zimmerman (2019) shows that students from elite high schools who attend top universities have a very high probability of having a very good job, compared to their college peers who did not attend elite high schools.

Chile is one of the richest countries in Latin America, having had significant GPD growth since 1980 (Corsetti and Schmidt-Hebbel, 1999; Schmidt-Hebbel, 2006) and reduced poverty (Contreras, 2003; Olavarria-Gambi, 2003), with a current GPD per-capita of US $15,300 in 2019 (World Bank, 2020). However, this growth has not been equally distributed, and Chile ranks amongst the most unequal countries in the world, with a GINI coefficient of .44 (Milanovic, 2016). Economic growth has been used on public policies to improve education and health, however that have not yet translated into income equality. Chile has shown important improvements in all levels of education, increasing the overall enrollment rate during the last 25 years (SIES, 2015). Early childhood net enrollment rates for children between 4 and 5 years old has reached 90% (CASEN, 2015). The gross primary and secondary education enrollment rate reached 104.1% and 99.6%, respectively in 2015. The net primary and secondary education enrollment rate reached 93% and 74% respectively that year. The significant increase in coverage has been sustained with with increased public expenditure in education and the use of public and private schools [7].

[7]at the secondary level, although the gross enrollment rate reaches 99.6%, the net enrollment rate only reaches 73.6%, suggesting a pronounced overage in this education level, due to important dropout and stop-out rates.

Despite this success in enrollment, challenges remain regarding quality, equity, and access to preschool. The Chilean school system is ranked in the third lowest in the Programme for International Student Assessment (PISA) performance among OECD countries and is above the average in the correlation between parental socioeconomic status and test scores (OECD, 2016). For example, on average, students in private schools performed significantly better than those in public schools. Moreover, students in the top 20% of socioeconomic status outperform their peers in the bottom 20%, with a gap equal to 3.5 years of schooling (OECD, 2016). At the same time, the early childhood care enrollment rate remains low compared to the OECD average, particularly for children age three or younger (OECD, 2016).

Enrollment in tertiary education expansion has been explosive, increasing the net enrollment rate from 12.8% in 1990 to 37.4% in 2015, and is still increasing (CASEN, 2015) [8]; this growth has been promoted largely by financial aid in the form of loans and scholarships and by the expansion of private sector colleges (SIES, 2015). However, the increase in higher education has not been homogeneous. While the highest income quintile has a net enrollment rate of over 53%, students from the lowest income one have a rate of 33%. Moreover, not all students have seen the same positive income effects from higher education as some earn the same or less then what they would earn with just a high school education (Bucarey et al., 2018; Urzúa, 2012). While nutrition and health are important factors for intergenerational mobility in other developing countries (Krishna and Nolan, 2019), they may have a much lower impact in Chile, as undernutrition has stopped being a problem and the public health system has advanced towards a system of guarantees, that offers health provisions for the population (Missoni, 2010).

III. Methodological Framework

A. Data Set

Developing countries historically had not have the investment and institutional stability to create long term nationally representative longitudinal surveys (Krishna and Nolan, 2019). However many countries have devoted important resources to their educational system, giving tests and surveys to a representative samples of the student population or in some cases, a whole cohort of students and their families. One advantage is that some countries, such as Chile, have full coverage of primary and middle school education. This paper takes advantage of the high coverage in middle school education in Chile and creates a data set that merges national administrative data sets and national surveys to create a comprehensive analysis of students' educational and work trajectories. The data

[8]The tertiary education system, including both university and vocational education, had 245,000 in 1990, and is currently nearly 1.3 million students

sets are listed in Table 1. The first data sets include school enrollment and test scores in 8th grade and high school, higher education enrollment, and higher education graduation. The first administrative data set include all the students in the country, even those at private and public institutions. The second set of administrative data set comes from the Ministry of Labor, and consists of the wages tracked by the Department of Unemployment Insurance of the Ministry of Labor; we use this to obtain salaries of the students from 2007 to 2018. The administrative surveys are the national mandatory SIMCE test, and the national voluntary College Selection test and are provided by the Ministry of Education and DEMRE (Department for the Educational Testing, Measurement and Records, of the University of Chile). Lastly, the wages of individuals in the public sector were downloaded from the Ministry of the Interior's transparency web page.

All these data sets allowed us to follow the students from 2004 to 2018, as described in Figure 1. The data sets collected can be organized in the next group of variables:

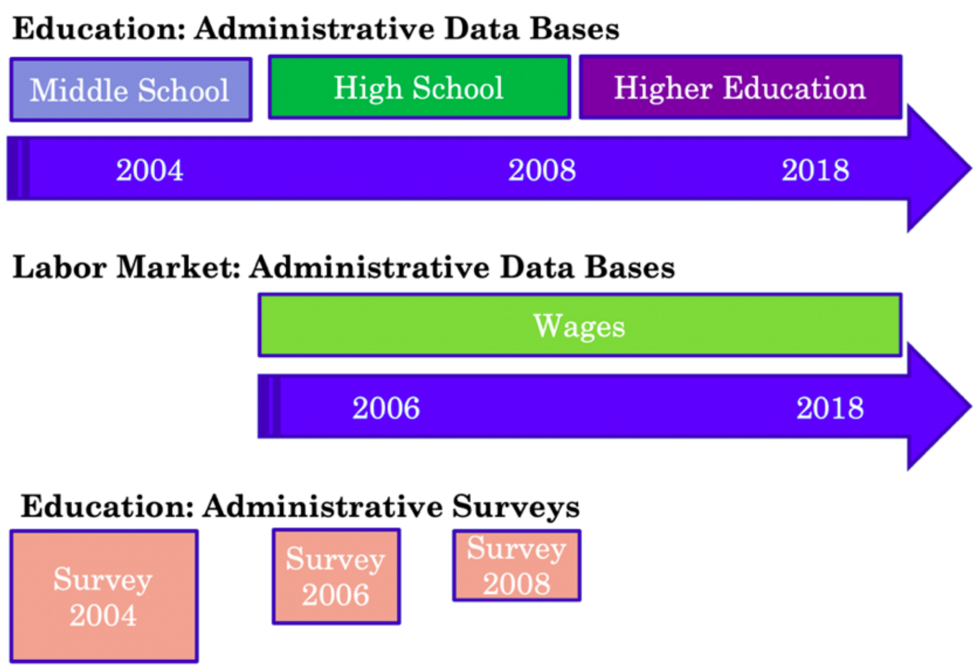


FIGURE 1. DATA SETS USED AND MERGED

Family Income and Education: These are the initial condition variables of these students. Family income is available for all the sample and parental educational level for over 84% of students. Parents recorded their family income level as one of 15 income brackets, and their educational level using twelve different categories.

Academic Outcomes: The academic outcomes of the students are high-school dropout, high school repetition, high school change, high school quality, and higher education enrollment and graduation. These variables are present for all students in the sample as the study relies on administrative data sets. These are the variables that are analyzed on a year-to-year basis. The national mandatory SIMCE test scores are also present for the initial year for each student to measure their academic performance.

School Social Class: The school social class proxy is the occupations of their fellow students' parents when they are in in high school. Other authors such as Torche (2005) adapted the occupational social class structure developed by Erikson, Goldthorpe and Portocarrero (EGP) for Chile (Erikson et al., 1979). The College Selection Test survey asks students the about their parents' occupations. Although not all students answer this survey (due to attrition and school repetition), we can obtain measures at the school level that consider the majority of graduating students similar to that of Canales (2016). This paper follows Canales (2016), who used the college selection test survey and an adaptation of Torche (2005) to classify the social classes of the parents of students taking the College Selection Test. In specific, the highest level occupations are used as a proxy of the highest social class of individuals. In this survey parents are classified according to twelve occupations, with the highest being: high level managers in firms, government managers, high level diplomats, high level justices or armed forces officials. In this paper we will focus only on this highest occupational category to generate a school level variable that would indicate the proportion of high class individuals in the schools.

School role models: Previous years of financial aid and college enrollment have been used in the Chilean literature as proxies of role models (Altmejd et al., 2020; Barrios Fernández, 2019; Blanco and Meneses, 2013), as younger students tend to mimic the patterns of financial aid and college enrollment of students from older generations in their schools. Following these previous examples, the areas of study of students and their college-major decisions will be used as proxies of role models. The main idea is that younger students in a school will tend to study the same professions and attend the same institutions as older generations of students from the same high school. In particular this paper will use the proportion of one older cohort of students who major in science, social science, or engineering, degrees that have been shown to lead to high wages in the labor market (Hastings et al., 2015).

Neighborhood: Neighborhoods are defined as the municipality of residence of the student. Previous literature has linked the neighborhood of individuals and intergenerational mobility (Chetty et al., 2014), therefore this variable will be included as a control.

Table 1 summarizes the main variables of this study. This presents the student wages, parental income, and the educational outcomes of both. Parental wages are available for 249 thousand students [9] . Maternal education is obtained from the SIMCE survey, and there is available information for 230 thousand students. There is wage information for 181 thousand students students for whom their income rank is calculated. Parental educational is measured in eight different levels. The social class variable, e.g. the proportion of parents who are high level managers, is only 2% of the sample. The role models variable, the high school indicator variable that estimates the proportion of students from older generations who studied sciences, social sciences or engineering, shows that on average 20% of older student got these degrees. It is important to explain that students who drop-out of high school or college, generally appear again in the wage data base, therefore, their are not a source of the attrition for this data base.

Table 1—Summary of Main Variables

	mean	sd	count	min	max	source
Academic Variables						
Years of Education	15.0	3.2	249373	8	21	Ministry Education
SIMCE Test Score 2004	253.2	47.1	249372	111.0	398.9	Ministry Education
SIMCE Tests Score 2006	258.7	53.7	184687	106.9	412.4	Ministry Education
Higher Education Enrollment	0.7	0.5	249373	0	1	Ministry Education
Higher Education Graduate	0.4	0.5	249373	0	1	Ministry Education
College Graduate	0.2	0.4	249373	0	1	Ministry Education
Vocational 2-year Graduate	0.06	0.2	249373	0	1	Ministry Education
Vocational 4-year Graduate	0.1	0.3	249373	0	1	Ministry Education
Sciences & Eng.Graduate	0.2	0.4	249373	0	1	Ministry Education
Income and Demographics						
Child Wage(US)	834.6	615.6	181885	0	5390.5	Ministry of Labor
Child Wage Rank	0.5	0.3	181885	0.000005	1.0	Ministry of Labor
Top 10 percent Income	0.10	0.3	181885	0	1	Ministry of Labor
Parental Income	530.8	708.7	249373	82.0	3770.5	SIMCE 2004
Parental Income Rank.	0.5	0.3	249373	0.000004	1	SIMCE 2004
Parental Education Level	2.0	1.1	224006	1	8	SIMCE 2004
Female	0.5	0.5	249373	0	1	SIMCE 2004
S.Class and Role Models						
Manager Parent	0.02	0.1	249373	0	1	College Selection Test
Manager Parents in 12th Grade	0.02	0.06	249373	0	1	College Selection Test
Role Models 12th Grade	0.2	0.14	249373	0	1	Ministry of Education

[9]According to the CASEN survey, there are 283,695 individuals of 26 years of age in 2017. The SIMCE test was planned for 280,753 students. and 249,373 parents answered the income question in the parental survey

B. Ranking Calculations

The ranking of children and parents is calculated to pursue a rank-rank analysis. First, the 249 thousand parents are sorted according to their income, and are given a value of 0 to 100 with 100 being the parent with the highest income and 0 the lowest income. Second, the children's ranking is calculated excluding the individuals with missing data The parents of the missing children are not excluded from the calculation. The remaining 181 thousand students are sorted according to their average wage in 2016, 2017, and 2018, and then are ranked between 0 and 100. This methodology is slightly different from Chetty et al. (2014) as they replace individuals with no income with zeros. Other papers for Chile, such as (Nunez and Miranda, 2010), also exclude individuals with no income, and those earning below the minimum wage. For this particular data set, replacing data with zeros will generate extremely low estimates, implying high social intergenerational mobility, something that would not be consistent with previous results or methodological approaches for Chile. Appendix I shows an analysis of the missing data, and how it relates to gender, parental income, and informal employment. In the following sections the consistency of this wage data is going to be tested using national surveys.

C. Methodology and Econometric Formulation

Once parental income rank and child wage rank are calculated, I proceed to estimate the intergenerational income mobility of students and include different control variables. A first step is regression on equation (1) estimates using the traditional methodology to estimate rank-rank regressions, - as in Chetty et al. (2014).

$$ChildRank = \beta_0 + \beta_1 ParentalRank + \epsilon$$

(1)

A second approach uses the traditional method of including educational outcomes in equation (2), but also includes social class and role model controls at the high school level. This regression intends to show that the original school environment of the students is correlated with intergenerational mobility, which could otherwise be attributed to educational outcomes.

Child Rank $= \beta_0 + \beta_1$Parental Rank $+\beta_2$Academic$+\beta_3$Role Models$+\beta_4*$Social Class$+\epsilon$
(2)

Then, the main analysis of this paper estimates the intergenerational mobility of students using a rank-rank regression specification incorporating year-to-year control variable. Equation (3) controls for all possible work and educational trajectories. To analyze students' trajectories, first, all possible educational and work profiles of the students are created, generating over 33 thousand different profiles. The objective of this methodology is to identify the differentiated impact of different educational and work trajectories. Then, the profiles that have more than 10 students are kept, leaving 592 profiles and replacing the other profiles with a constant.

$$\text{Child Rank} = \beta_0 + \beta_1 ParentalRank \sum_{j=1}^{592} \beta_j * \text{ Trajectory} + \epsilon \tag{3}$$

IV. Results

A. *Intergenerational Mobility Estimation:Comparison With National Surveys*

This section will compare the results of the novel panel data set with national surveys used in Chile. Table 2 shows the descriptive statistics of the wages of individuals from the CASEN survey 2017 and the wages of the panel data set. The results show that the wages of the Panel Data set are 7% higher and have a lower standard deviation compared to the survey. It's possible to see that the panel data set identifies individuals with higher wages, with a higher maximum three times as high as the one from the CASEN survey. This is a problem of the CASEN survey, that historically has not been able to survey higher-income individuals in the population (Programme, 2017). The lower standard deviation could be caused by the average of the wages during 2016, 2017 and part of 2018. Using the wages, the rankings of the individuals are calculated for both data sets.

As a next step, OLS regressions are used on equation (1) using the administrative panel data set show the relationship between child wage rank and parental income rank. Table 3 shows these regressions. Column (1) compares the results with the entire sample, finding a coefficient of .2, a low estimation compared to other countries in the literature, slightly above that of Scandinavian nations but lower than the USA(Chetty et al., 2014). This results would be out of the norm, as previous papers had shown that Chile had less intergenerational mobility than

Table 2—Comparison Between National Survey CASEN and Panel Data

Source	(1) Mean	(2) SD	(3) 10%	(4) 25%	(5) 50%	(6) 75%	(7) 90%	(8) Min	(9) Max
CASEN Survey	504,936	473,738	185,000	274,167	380,000	600,000	950,000	500	1,150,000
Panel Data	539,484	394,111	170,206	288,925	431,250	688,915	1,022,850	0	3,493,000
Difference	7%	-17%	-8%	5%	13%	15%	8%		

Casen Survey Individuals 27 years old in 2017.
Panel Data set, average wage 2016, 2017 and part of 2018.

the US (Nunez and Miranda, 2010). Columns (2)-(5) show the same calculations, but for individuals originally from different income quartiles. The results seem puzzling, as they show high mobility for quartiles Q1, Q3 and Q3. However, the coefficient seems to be high (.729) for higher-income families. These would mean that there is high mobility amongst the lower income groups of the population, but a very high transmission of income for the higher income groups. Previous authors had mention that the rank-rank slope had the advantage to have a linear relationship (Chetty et al., 2014), however it does not seem to be the case in Chile, and is likely that this assumption should be tested in other highly-unequal developing countries.

Table 3—OLS Regressions: Adult Wages and Income Quartiles

VARIABLES	(1) Full Sample	(2) Q1	(3) Q2	(4) Q3	(5) Q4
Parental Income Rank	0.204***	0.179***	0.0455***	0.184***	0.729***
Constant	0.404***	0.415***	0.475***	0.396***	-0.0303*
Observations	181,885	46,062	47,315	45,549	41,094
R-squared	0.041	0.005	0.000	0.008	0.032

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

To review the validity of the administrative data set, and the possible problems of the missing data, I replicate the analysis using the national CASEN survey from 2017. The CASEN survey is a nationally representative used to analyze the country and guide public policy in Chile. It's also the source of information that previous studies used to estimate intergenerational mobility in Chile (Nunez and Miranda, 2010; OECD, 2018) Synthetic parents are created using the educational levels from the survey and the parental household income is used if the individuals did not answer the survey[10]. The results show a very similar overall pattern of

[10]The usage of the effective wages is necessary to be able to have enough data to perform the regressions

mobility (0.208 for CASEN, and 0.204 for the administrative data). The similarity of the results obtained using the CASEN 2017 survey and the administrative data suggest that the administrative data provides consistent results, even with the missing data due to informality. Once we start to look in more detail, the results for income quartiles (1) to (3) are different reversing the estimations. Q1 and Q3 have low estimates in the CASEN survey (0.037 and 0.005), while Q2 has a high estimate (0.209). The result for the highest income group, Q4, is high at (0.597), however, lower than the estimate from using the administrative data. This could be a weakness of the survey [11]. This differences per income quartiles could be due to the synthetic fathers' assumptions, which do not allow for the division of the population into smaller groups, while the administrative panel data set has detailed information on parental income.

Administrative data sets used to measure intergenerational mobility are particularly susceptible to two bias: life cycle bias and transitional income bias (Mazumber, 2016). Life cycle bias refers to the fact that income increases during one's life time, and students graduating from higher education could have very volatile wages early in their careers and high wage increases afterwards. Transitional income bias refers to the fact that using wages during a short period of time could capture a momentary shock in an individual's income. Both factors increase the estimation of intergenerational mobility. To attenuate life transitional bias I will use the average of three years of wages of students (2016, 2017 and part of 2018).

Table 4—OLS Regressions: CASEN Survey 2017. Individuals 25-30 years old

VARIABLES	(1) Full Sample	(2) Q1	(3) Q2	(4) Q3	(5) Q4
Parental Income Rank	0.208***	0.0375***	0.209***	0.00542	0.597***
Constant	0.401***	0.448***	0.377***	0.506***	0.0773***
Observations	1,658,524	368,017	401,238	425,028	464,241
R-squared	0.045	0.000	0.003	0.000	0.028

Observations represent the expanded population
*** p<0.01, ** p<0.05, * p<0.1,

To analyze the problem of the life cycle bias I use the CASEN survey. Figure 2 shows the comparison between the rank-rank income relationships estimated using the administrative data sets and the CASEN survey 2017. In Figure 2, the line represents the average child rank for each percentile of parental rank and for different age groups. It's possible to see that the curves tend to have a

for each quartile group

[11]All individuals with available data are included, including those making less than the minimal wage

similar behaviour. However, the curves do not seem to have small changes when there are changes in the years of the analyzed sample. This would mean that the estimations will be different for different age groups.

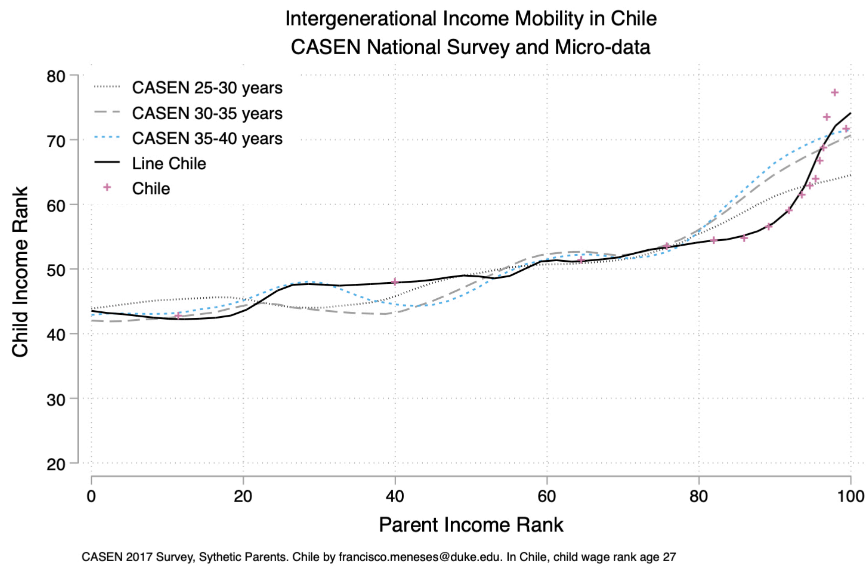


Figure 2. Intergenerational Income Mobility in Chile

With the intention to analyze the possible life cycle bias, Table 5 shows the rank-rank regressions using the CASEN survey for individuals from different age groups. It's possible to see that the full sample size obtains a coefficient of 0.238, while for the 25-30 year old group, the coefficient estimated is 0.21. Moreover, the estimated coefficient starts to increase for older age groups, which is consistent with the literature (OECD, 2018). Although the CASEN survey analyses individuals from different cohorts, and this survey does not follow the same cohort over time, it's possible to expect that the administrative data is going to present downward biased results, compared to the long-term estimate, as students are analyzed at 27 years-old, that is the maximum available age in the administrative data set. Therefore, the results of this paper using administrative data should not be considered the long term rank-rank intergenerational income mobility, but rather the early life estimate.

Table 5—OLS Regressions: CASEN Survey 2017

VARIABLES	(1) Full Sample(25-40)	(2) 25-30	(3) 30-35	(4) 35-40	(5) 30-40
Parental Income Rank	0.238***	0.208***	0.268***	0.262	0.251***
Constant	0.369***	0.401***	0.355***	0.364***	0.388***
Observations	3,740,295	1,658,524	1,345,105	1,222,955	2,338,712
R-squared	0.06	0.0429	0.076	0.072	0.059

Observations represent the expanded population
*** p<0.01, ** p<0.05, * p<0.1,

Synthetic Fathers

This box explores the use of synthetic fathers using the administrative data sets of this paper. Synthetic fathers are the traditional measure of international mobility in the literature. To generate synthetic fathers a two step approach is followed. First, using CASEN 2006, the average male wage is obtained for men between 40-50 years old, based on their educational level. In a second step, this income is imputed to the fathers of the students in the sample. The average student wage in 2018 was of 631 thousand pesos, while the predicted paternal wages are of 384 thousand pesos. Then both wages are transformed to logs. The table below shows the Intergenerational Elasticity (IGE) estimates using the synthetic fathers and student wages in 2018. The results show an IGE estimate of 0.426, below previous estimates from the literature (0.53 from (Nunez and Miranda, 2010)), but high compared to developed countries. The results also show that the IGE estimate is higher for female students compared to their male counterparts.

OLS Regressions: Log Wages 2018 and Log Income Synthetic Fathers

VARIABLES	(1) Full Sample	(2) Male	(3) Females
IGE	0.426***	.379***	0.496***
Constant	7.667***	8.319***	6.690***
Observations	120,849	67,636	53,213
R-squared	0.041	0.0320	0.0574

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

The estimates using synthetic fathers are very different from the ones using rank-rank regressions. This is not the first document to present this puzzle when using Chilean data. The OECD found a similar pattern, estimating a high IGE for Chile (and low mobility), but at the same time high mobility using quartiles and panel data set (OECD (2018) page 28 for quartile movement and page 36 for IGE). Several methodological and data changes could explain these differences. The first is the changes in levels and variance in the students' income. The children have higher wages than their parents, affecting the level and variance increasing the IGE. Moreover, the rank-rank estimations in this paper use the income of both parents while the synthetic fathers only use the fathers' expected income. The use of surveys to obtain information is also a source of variation as not all individuals answer the parental education survey. As an example, previous years of the CASEN survey had missing information for 50% of respondents parental education question (CASEN 2006) like in Nunez and Miranda (2010). To solve this issue researchers had to re-construct family trees to obtain the fathers' education level and re-estimate the intergenerational mobility in Chile (like in OECD (2018)). As a simulation I modify the student wages to have the same level and variance as their synthetic parents; the estimated IGE is of 0.25, well below the 0.43 just estimated. Overall, the results of this box show that students' wages from the panel data set provide an IGE estimates slightly lower than previous findings in the literature (Nunez and Miranda, 2010).

Figure 3 shows the comparison of rank-rank results in Chile, Italy, and Spain. The graph shows the average adult-child income rank for each parental income rank percentile. These paper analyzing these three countries use administrative data to calculate intergenerational mobility. The results show that Chile is very similar to Spain, with high mobility for individuals in the lowest 80% of the population, but also high "stickiness" or transmission of income in the upper part of the distribution. In particular, the Chilean income distribution shows very low mobility (or a high slope) for individuals whose parents were in the top 10% of the distribution. As explained by Bratberg et al. (2016), it is possible that a single indicator (or a linear one) is not able to fully transmit the complexity of social mobility in countries with low mobility in the extremes. Therefore, it could be possible that only looking at the rank-rank coefficient could not be enough to understand intergenerational mobility in Chile, and other estimates (like the IGE) could provide more information.

It's also important to note that the Chilean and Spanish results do not show stickiness at the bottom of the distribution, while the results from Italy do present a change in slope. This is likely due to a failure of the data on parental and child income (taxes for Spain and unemployment insurance in Chile), and not the country itself. Both studies have data limitations; the Spanish data set lacks information on the 40% of children who did not declare income, while the current paper lacks data for 27% of the children that do not work or do not work in the formal sector. Missing data is a problem for research using administrative data sets; Appendix II compares the estimates and missing data from different countries.

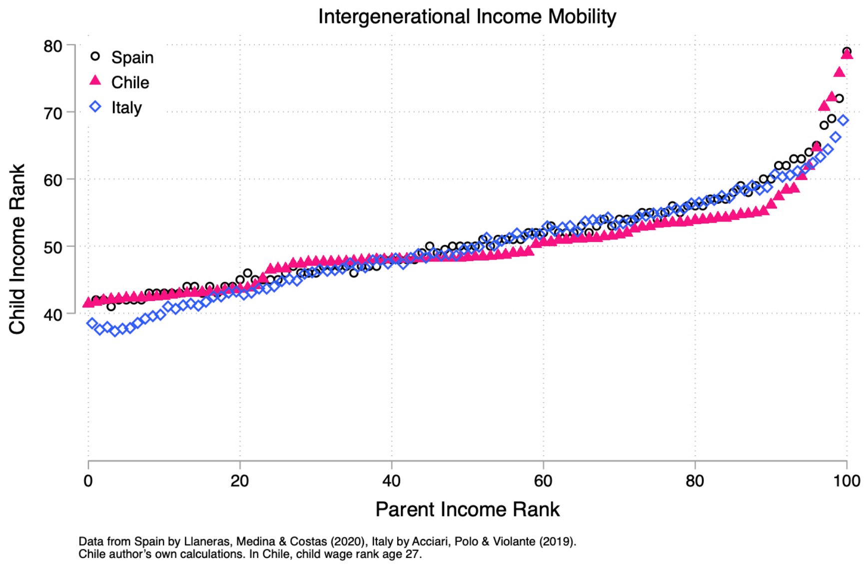


FIGURE 3. INTERGENERATIONAL INCOME MOBILITY IN THREE COUNTRIES

B. *Climbing the Mobility Ladder*

Transition matrices analyze how students succeed or not in the mobility ladder by analyzing income mobility of parents and children. Table 6 shows the transition matrix of students, dividing them into four income quartiles for parents and children. The parental quartile shows where the students started, and the child quartile shows where students are located at age 27. The transition matrix shows that there is "stickiness" at both extremes. Individuals in the lowest income quartile have a 29% probability of remaining in that quartile, and a 16% probability of reaching the top quartile, while high-income individuals have a 42% probability of continuing in the same quartile. Note that previous estimates from the literature have shown even more mobility in Chile. Using the CASEN Panel Survey, the OECD found that low income individuals had a 25% probability of remaining in the low income quartile and a 23% probability to enter the top one (OECD, 2018). [12]. Analyzing occupations, Torche has found fluidity in the Chilean society but downward rigidity for higher occupational groups (Torche, 2005). Although these results are also similar to a paper using administrative data in Scandinavian countries (Bratberg, 2014), it's important to mention that this income quartiles hide important variations that will make the IGE or rank-rank coefficients differ.

Table 6—Income Transition Matrix

		Adult Income Age 27			
		q1	q2	q3	q4
Parental Income	q1	29%	30%	25%	16%
	q2	24%	26%	26%	23%
	q3	24%	26%	25%	25%
	q4	20%	17%	21%	42%

While the transition matrix analyzed the movement between quartile groups, it could be useful to investigate the individuals from all income groups who reach the top 10% of their cohort measured in wages. Figure 4 (left) shows this proportion of students. It is possible to see that 40% of the students who are in the top 10% are from the fourth income quartile and have tertiary education. It seems that proportionally, higher education is correlated with high income students reaching the top ten percent, something that will be reviewed later.

In Chile, while children in all income groups had important gains in educational achievement, access to higher education is still stratified. Figure 4 (right) shows that while 89%of the students in the highest income quartile had enrolled in higher education, only 44% of students in the lowest income quartile did. Moreover,

[12]These results found by the OECD show a high mobility for Chile, similar to countries such as Denmark, Portugal, or Great Britain OECD (2018)

while the majority of low-income students access vocational education, higher-income students were much more likely to enroll in college. Additionally, while the difference in higher education access is very high, the proportion of low-income students who reach the highest 10% income group of their cohort is even lower, compared to individuals from the highest income quartile.

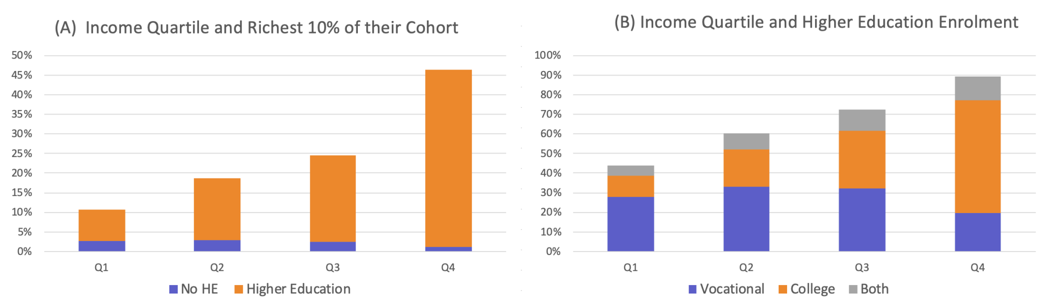
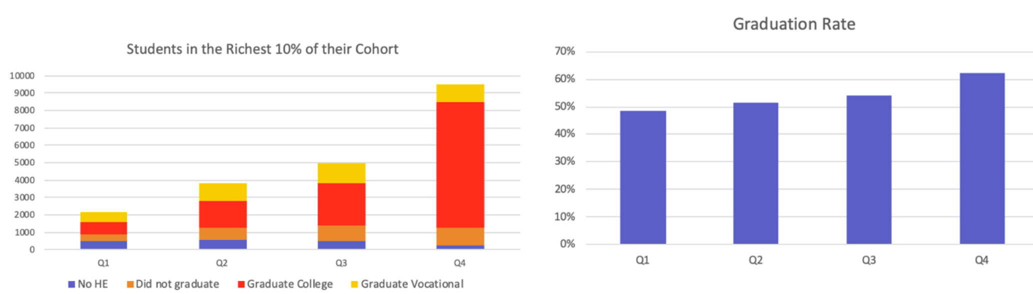


FIGURE 4. HIGHER EDUCATION ENROLLMENT, TOP 10% IN WAGES AND INCOME QUARTILES

Figure 5 (left) shows that for students who reach the richest 10%, most of them graduated from college. Figure 5 (right) shows that low-income students graduate at a lower rate. Therefore, we have identified our first factors correlated with intergenerational mobility roadblocks; low-income students have lower higher educational enrollment, lower college enrollment, and lower graduation rates.



Income quartiles calculated from parental survey in 2004.

FIGURE 5. HIGHER EDUCATION ENROLLMENT TYPE, GRADUATION RATES AND INCOME QUARTILES

Even after graduating from college, low-income students face several challenges. One is that they tend towards majors that are rarely found in the richest 10% (Appendix III). In Chile, students choose their college major before enrolling in college and have almost no possibilities to change later. Thus this is a factor that is associated with their high school environment, not their higher education one. Low income students will tend to study degrees and programs with lower profitable, even when having College Selection Test scores that allow them to attend other programs.

C. Academic Outcomes, Social Class, and Role Models

Role models in school have been proven to be a relevant factor in educational decisions (Altmejd et al., 2020; Barrios Fernández, 2019; Blanco and Meneses, 2013), and there are similar arguments about social class of origin as well (Bourdieu, 1986). This subsection will analyze the correlation of academic outcomes, role models and social class on intergenerational income mobility. First, the maximum educational level attained by each student will be used as a control variable as it is in other papers in the literature (Chetty et al., 2017). Second, a social class and role model proxy will be created at the high school level. The first indicator measures the proportion of older classmates in each school who graduated successfully from high wage majors (engineering, the sciences, and social sciences). The proxy of social class will be the proportion of fellow students whose parents who are high level managers. Meanwhile, the student's academic quality is controlled for by using the 2004 SIMCE test scores.

Table 6 shows that the results considering five different specifications. Column (1) includes the students' academic outcomes, showing that increased educational achievement is correlated with upward intergenerational mobility. In particular college graduation is associated with a .235 rank increase. Column (2) and Column (3) include social class controls and the SIMCE test scores.The results show that the inclusion of social class and role models proxies have a positive and significant coefficient and furthermore, reduce the college coefficient. Column (4) includes a municipality dummy variable, to control for neighborhood environments. The proxies of social class and role models are correlated with higher students' income rankings, even when controlling for the SIMCE test scores at the student level and school level. The results for the 8th grade SIMCE test score show that higher test scores increase the probability of upward intergenerational mobility. The proxies of social class and role models continue being significant after the municipality and quality controls are included. Column (5) includes the SIMCE test score at the school level and a multiplicative variable between the social class proxy and college education. The interaction effect between social class and college is positive and significant, meaning that being enrolled in a higher-class school is associated with higher intergenerational mobility once the students attends college, similar to the results of Zimmerman (2019). The results also show that the inclusion of the social class and role model proxies increased the adj-R-squared, increasing the explanatory power of the model, over model in column (1). This increase in the adj-R-squared or explanatory power, lead to the conclusion that regressions that include only parental income ranking and educational outcomes could be lacking other important social components - as social class - that should be included in future research.

TABLE 7—OLS RESULTS: ACADEMIC OUTCOMES, ROLE MODELS AND SOCIAL CLASS

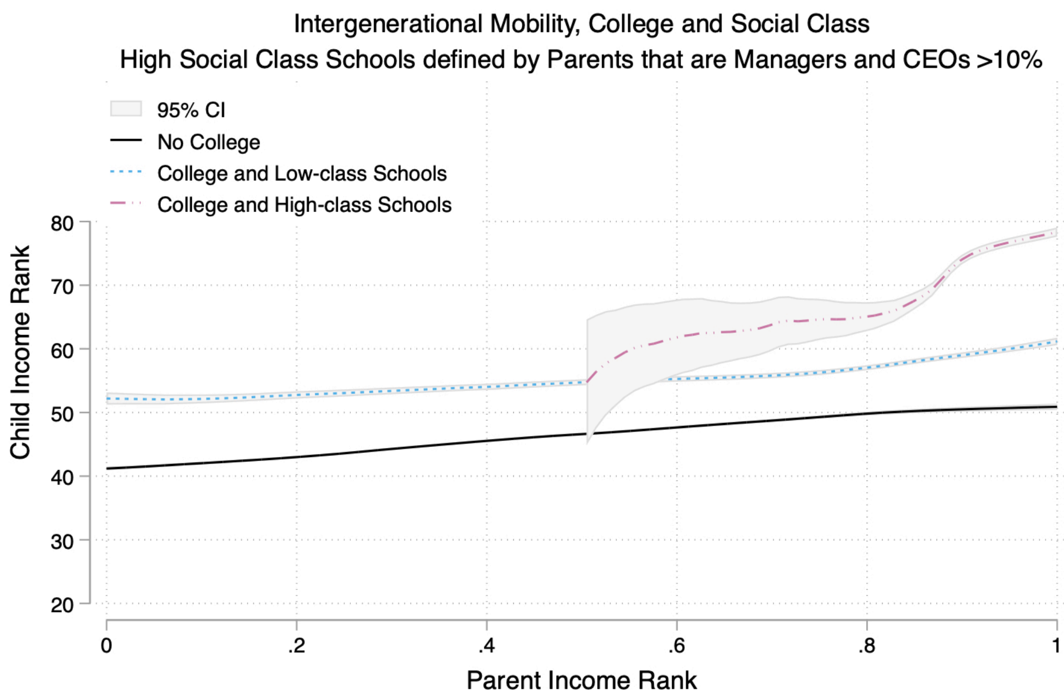
VARIABLES	(1)	(2)	(3)	(4)	(5)
Parental Income Rank	0.0802***	0.0468***	0.0418***	0.0109***	0.0143***
Middle School	-0.0843***	-0.0754***	-0.0710***	-0.0663***	-0.0661***
9th Grade Drop-out	-0.0819***	-0.0723***	-0.0694***	-0.0684***	-0.0680***
10th Grade Drop-out	-0.0733***	-0.0628***	-0.0608***	-0.0603***	-0.0598***
11th Grade Drop-out	-0.0565***	-0.0454***	-0.0454***	-0.0444***	-0.0438***
HE Freshman Drop-out	0.0480***	0.0462***	0.0421***	0.0299***	0.0303***
HE Sophomore Drop-out	0.0298***	0.0276***	0.0239***	0.0172***	0.0175***
HE Junior Drop-out	0.0400***	0.0369***	0.0325***	0.0271***	0.0274***
HE Senior+more Drop-out	-0.0188***	-0.0265***	-0.0347***	-0.0358***	-0.0345***
Vocational Graduate	0.113***	0.104***	0.0971***	0.0981***	0.0987***
College Graduate	0.235***	0.204***	0.188***	0.195***	0.192***
Role Models Proxy		0.128***	0.0870***	0.114***	0.123***
Social Class Proxy		0.337***	0.324***	0.256***	0.119***
SIMCE Test Score 2004			0.000417***	0.000427***	0.000449***
SIMCE Test School					-0.000129***
Social Class & College					0.189***
Municipality	no	no	no	yes	yes
Constant	0.400***	0.395***	0.307***	0.367***	0.391***
Observations	181,885	181,885	181,884	181,884	181,884
Adj-R-squared	0.151	0.158	0.161	0.182	0.182

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

Figure 6 shows a pattern similar compared to Table 7, column (5), where students from higher class schools who attend college have an higher curve compared to those who went to college, but went to regular high schools. These results suggest that students attending higher class high schools tend to have less intergenerational downward mobility, a higher slope, and a higher rank level.

Overall, the results in Table 7 also show that the inclusion of the proxies for role models, social class, and SIMCE test scores reduces the college graduation coefficient's magnitude and increase the adjusted-R squared. The results also show that social class of origin and school environments are related to changes in intergenerational mobility, particularly higher income ranking for the students, and lower mobility (as higher income students attend higher class schools). Therefore, it is possible that previous studies that did not include factors such as social class or high school environment, (like Torche (2011); Palomino et al. (2018); Chetty et al. (2017)) could be overestimating the impact of college on intergenerational mobility as they did not control for previous school and social class environments.

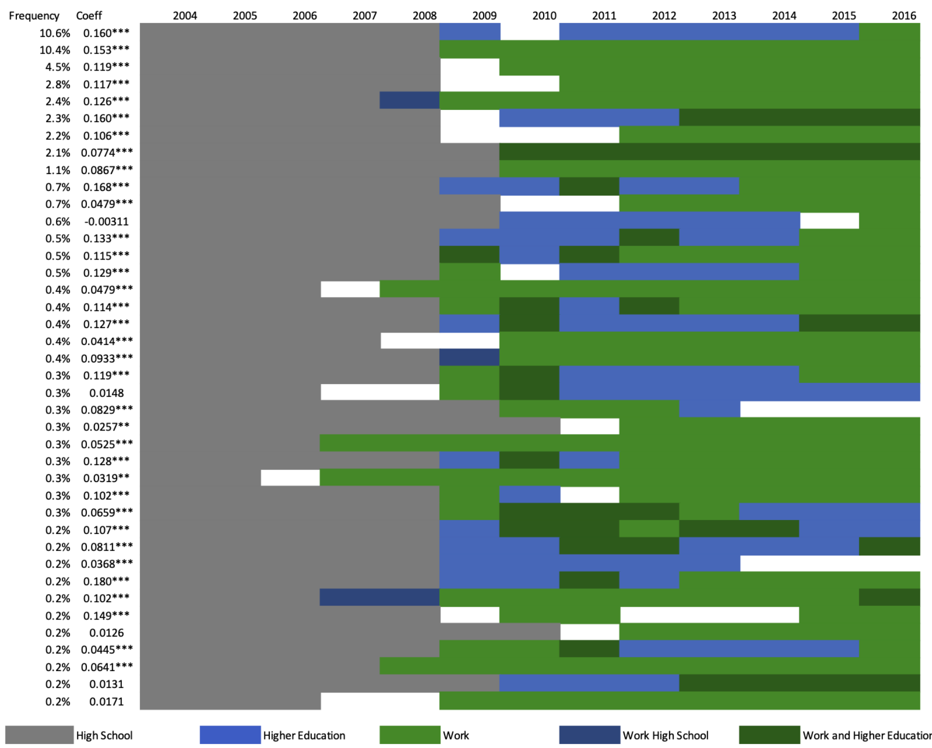
Figure 6. Intergenerational Income Mobility, College and Social Class Proxy



D. Year-to-Year Analysis

Besides test scores, educational environments, and social class, students' educational and work trajectories could also influence their intergenerational mobility. This section will perform a year-to-year analysis of their actual educational and work trajectories . To analyze the student trajectories, the regression includes 592 possible profiles. These profiles were chosen as they each represent 10 or more students.

Figure 7. Most Frequent Profiles: Coefficient for Joint Trajectories



The OLS regressions are performed with students in middle school as the base of the analysis (Appendix IV). Figure 7 shows the forty most common student profiles. There is a great diversity of possible educational and work profiles. It's possible to see that in seven of the categories, students have a gap year before they enter higher education or start working. However these profiles are not the most profitable ones in terms of intergenerational mobility. Figure 8 shows the 40 profiles that provide the highest returns in terms of income rank in their cohort. Note that the majority of these profiles do not have gap years, and start and end soon higher education, and include a steady work trajectories. The top trajectories have the characteristic of direct high-school to higher education transitions, direct higher-education to work transitions, and a steady work pattern. This means that gap years are negatively correlated with higher income mobility. Moreover, the majority of these profiles include a mixture of work and high school education and work and higher education done at the same time, therefore it could be possible that there are positive externalities of working and studying. However, it's possible that these success profiles correspond to different types of individuals.

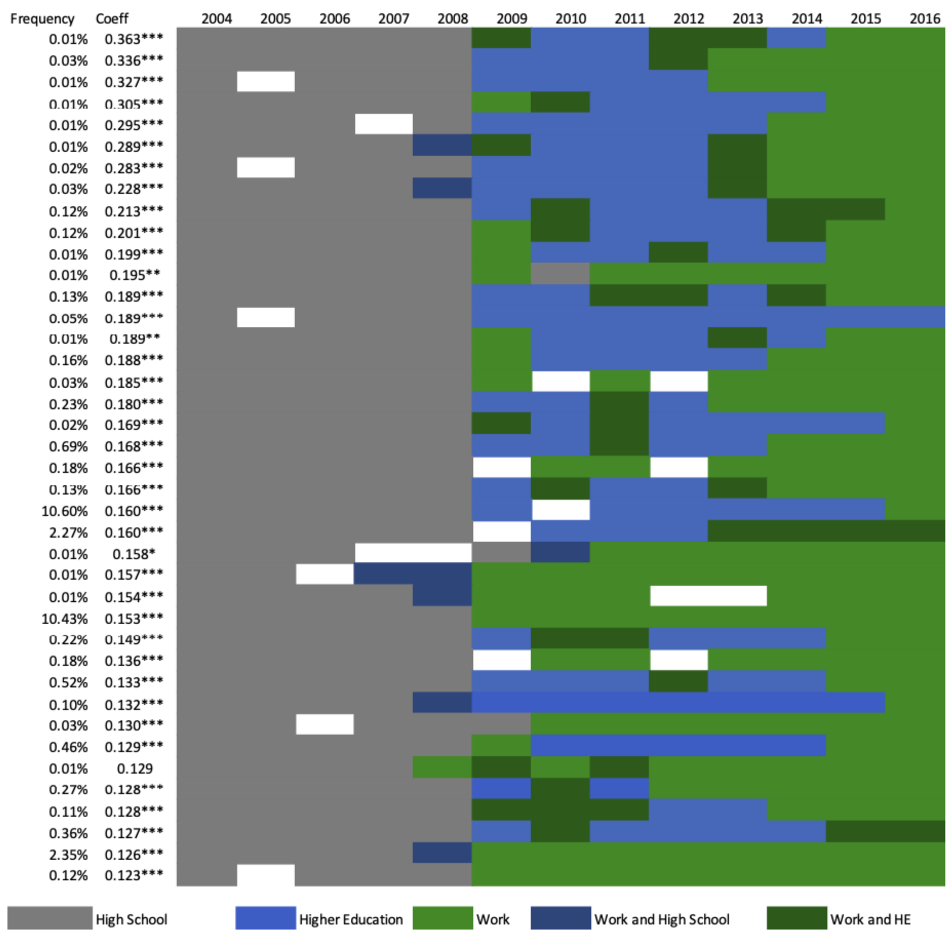


Figure 8. Top 40 Profiles: Coefficient for Joint Trajectories

Figure 9 shows the top 20 profiles, that generate more income mobility, for students in the top income quartile in 8th grade. Figure 9 shows that nineteen of these profiles include higher education, and 16 include a steady and stable work profile, with no gap years. For higher income students, then, higher education seems to associated with upward social mobility. Moreover, it's possible to see that most of these profiles include a steady high school education, only three include high school and work, however many include higher education and work at the same time. Overall, these profiles seems very "traditional" in the sense that students graduate high school on time, attend higher education, and then work, without gap years.

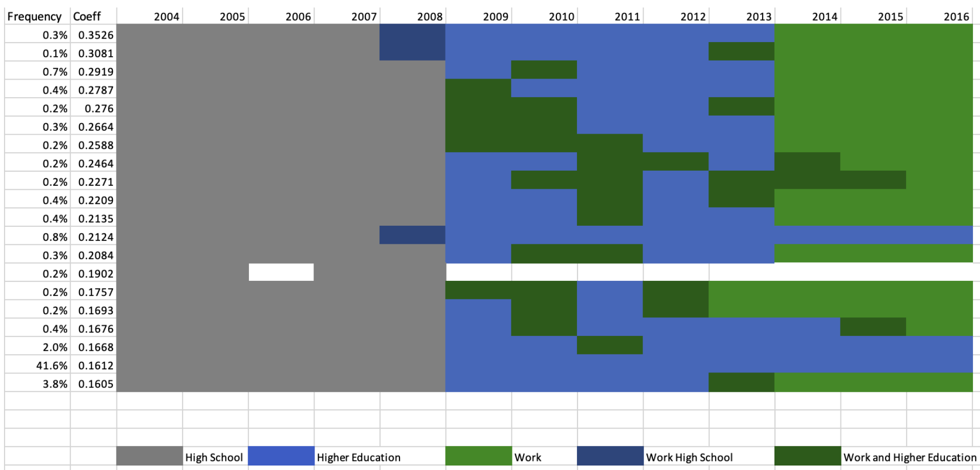


FIGURE 9. TOP QUARTILE INCOME FAMILIES: TOP 20 PROFILES: COEFFICIENT FOR JOINT TRAJECTORIES

Figure 10 shows the top profiles, for individuals in the bottom income quartile in 8th grade. The results are extremely different compared to their high-income counterparts. Only three out of the twenty profiles include higher education. Eighteen out of the twenty profiles include steady work patterns after high school and higher education. Most of these profiles do not include gap years, showing that a stable labor market is associated with upward mobility.

The analysis then shows that while, for high income students, upward mobility is achieved mainly thru higher education, for lower income students, the higher mobility is achieved mainly throughout the labor market and in particular, a stable work pattern, without gap years.

These results would point out in the same direction as the findings from the previous section, that found that higher education was more effective to promote mobility amongst individuals from high-class schools. Moreover, from a policy perspective, the conclusions to promote social mobility for different types of individuals could be different. While for high income individuals, a stable higher education seems key, for low income individuals, a fast labor market integration and labor stability are crucial.

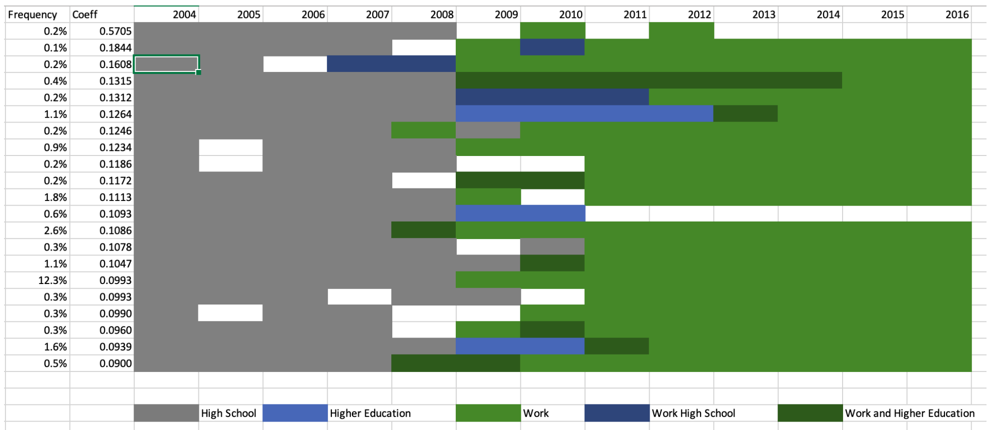


Figure 10. Bottom quartile income Families: Top 20 Profiles: Coefficient for Joint Trajectories

Figure 11 shows the education and work trajectories that have the lowest returns in terms of rank. In general these profiles have students not finishing high school or finishing it in an irregular pattern. These are the students that have failed in the educational system and in the labor market; having problems to finish high school and to keep a stable work. further research should focus on the social variables and shocks that these students are facing, and propose policies that would help these individuals to effectively attend high school and successfully integrate themselves to the labor force.

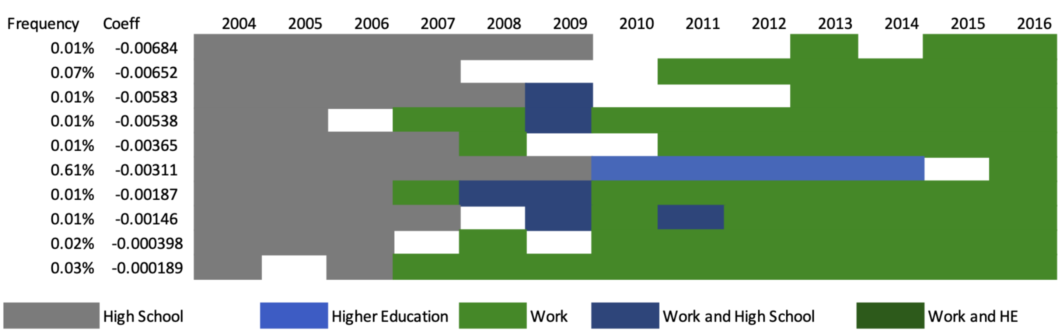


Figure 11. Bottom 10 Profiles: Coefficient for Joint Trajectories

The results of this subsection show that while higher education is important, the profile of education and work are also relevant in achieving upward intergenerational mobility. Profiles of students who are able to maintain a steady educational and work profile, with no gap years, are correlated with the highest increases in intergenerational income mobility. Although previous studies have shown that higher education stop-out (taking a gap year or changing programs) is not necessarily correlated with lower graduation rates (Blanco, 2018), these trajectories seem to have intergenerational mobility effects.

E. External Schocks: Parental Unemployment

Previous the section analyzes difference between achieving social mobility for individuals coming from different income groups. In contrast, higher education has, on average, a positive significant and stable impact on income mobility for higher-income students, while lower-income students find a better strategy by going directly to the job market. The higher education strategy may have higher variance but a lower average impact for low-income students. These results mean that without changes in the higher education effectiveness, on average, a stable labor market seems to be a better strategy to promote early income mobility for lower-income students.

Higher education drop-outs and stop-outs could in part explain the lower average results for lower-income students. Higher education drop-outs and stop-outs could in part explain the lower average results for lower-income students. Further research should analyze if these differences in intergenerational mobility estimates persist over time or if students with irregular educational and work patterns can eventually catch up with their peers.

While the main results of this paper a descriptive, the creation of a year-to-year data set creates the opportunity of causal analysis. The next section shows for a sub-sample of students how external shocks - parental unemployment - reduce the intergenerational income mobility of female students, in particularly when parents face unemployment.

To show the capabilities of the year-to-year data set, this paper analyzes the impact of negative shocks for a convenient sample of individuals for whom we have parental employment information. In particular, a negative economic shock is defined as six or more months of unemployment, if in the previous month the parent worked more than six months. This analysis is performed for the sub-sample of students that applied to higher education in 2008. The regression results in the Table bellow show that the impact of the economic shocks on social mobility are negative, particularly in two points in the life of the individuals: the final year of high school, and the final year of college (as college in Chile tends to last more than four years). The table bellow shows the rank-rank analysis differentiating male and female students. Columns (1) and (2) show that the negative effect of the shock affects mainly female students. These results open space for new questions , to ask about the mechanism of transmission of these negative shocks and how could they be prevented.

Table 8—Year to Year Analysis of Intergenerational Mobility and Parental Unemployment and Gender

Variables	(1) Male	(2) Female
Rank Father	0.138***	0.208**
	(0.01)	(0.01)
Shock -11th Grade	-0.00916	-0.0048
	(0.01)	(0.01)
Shock -12th Grade	-0.00306	**-0.0179***
	(0.01)	(0.01)
Shock -HE Freshman	-0.0123	-0.00119
	(0.01)	(0.01)
Shock -HE Sophomore	0.00701	0.00177
	(0.01)	(0.01)
Shock -HE Junior	0.00435	-0.005
	(0.01)	(0.01)
Shock -HE Senior	-0.0025	-2.17E-05
	(0.01)	(0.01)
Shock -HE Senior +1	-0.0137	**-0.0210****
	(0.01)	(0.01)
Shock -HE Senior +2	0.00356	-0.007
	(0.01)	(0.01)
Shock -HE Senior +4	-0.00561	-0.0115
	(0.01)	(0.01)
Shock -HE Senior +5	-0.00763	-0.00176
	(0.01)	(0.01)
Observations	34,705	43,661
R-squared	0.016	0.037

V. Conclusions

This paper is one of the first attempts to estimate intergenerational mobility in a developing country using administrative data sets, tackling data limitations as well as the emergence of results that generate new puzzles.

The analysis using administrative data and the national CASEN survey found that the administrative datasets and the CASEN 2017 survey generate similar results for individuals of the same age group, with a rank-rank coefficient of 0.20. The IGE estimates for Chile were found between 0.43-0.53 (Nunez and Miranda, 2010), while the rank mobility estimates found are between 0.20-0.26 for different age groups. This big difference in intergenerational mobility estimates between this paper and previous papers could be explained by the changes in level of income and income variance of the children, the assumptions in the creation of synthetic fathers, and particular characteristics of Chilean society.

Overall, using transition matrices and rank-rank regressions, the results of this paper show that there is fluid intergenerational mobility in Chile. However, there is "stickiness" for higher-income groups, presenting high rank-rank correlations (0.79) compared with the lower income groups. These results are in line with previous intergenerational mobility results for Chile (OECD, 2018; Torche, 2005) that present a mobile society with a rigid upper class.

The results of this paper showed the strenghts of detailed administrative datasets. Using OLS regressions, the association between academic outcomes and intergenerational mobility are tested. Taking advantage of detailed individual and school level information, this paper analyzed the inclusion of academic quality, social class, and role models proxies, and municipality controls. The results showed an association between these controls and intergenerational mobility, increasing their explanatory power, and reducing the estimated association with college education. These results highlight the importance of neighborhood and school environments. Moreover, it suggests that previous papers that do not include environmental or school controls could be overestimating the correlation of college and intergenerational mobility.

The year-to-year analysis of educational and labor market trajectories showed there are many possible educational and work trajectories that students could have, however not all of the trajectories that include pursuing higher education are as effective. In particular, trajectories that include higher education but also include a gap year are associate with lower mobility. While trajectories that included direct high school to higher education transitions and direct higher education to work transitions were related to higher intergenerational mobility. Moreover the year-to-year analysis showed that lower-income students find on average better results by integrating directly to the labor market than by pursuing the higher-education strategy, while the higher education strategy could provide for a higher variance. The higher variance but lower average effect could explain in part why an important proportion of students from the lowest quintile reaching the highest income decile have a college education and also explain why so few low-income students get to the highest income decile. Higher education seems to be providing a risky path for low-income students towards social mobility. Lastly, external negative shocks, such as parental unemployment, showed to have a negative effect on female students.

The utilization of administrative panel datasets and year-to-year analysis opens space for new research, as detailed questions can be answered, beyond classifications our outcomes, but the trajectories that individuals take. From a policy perspective, these year-to-year analysis shed light on the negative effects of slow or failed transitions between high school, higher education, and work, as well as gap years. Further research needs to be done in this arena to analyze the causes and long term consequences of these slow transitions that are initially associated with lower intergenerational income mobility.

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VI. Appendix I

This paper has 27% of missing data. As a first approach the table bellow shows the proportion of student with missing data. We see a patter of missing data for females and high income males. This pattern of missing data gets reduced slightly when we consider higher education as a control, as a small proportion of individuals continue studying and do not working.

FIGURE 12. NO

	No Wage				No Wage & No Higher Education		
	Total	Female	Male		Total	Female	Male
Q1	26%	33%	18%	Q1	26%	34%	17%
Q2	24%	31%	18%	Q2	24%	31%	17%
Q3	25%	30%	20%	Q3	24%	29%	19%
Q4	33%	35%	31%	Q4	29%	31%	26%
Total	27%	32%	22%	Total	25%	31%	20%

The missing data has two sources, individuals that are Not working, in Education or Training (NEET) and individuals in the informal sector. To analyze informality and NEET I use the National CASEN survey and re-created the methodology of synthetic fathers. Then I classified students according to the expected income of their fathers. The table bellow shows the proportion of informal workers in four income quartiles. It's possible to see that they distribute evenly across income groups.

Figure 13. Informal Workers in Chile

	Male	Female	
q1	11%	10%	11%
q2	11%	12%	12%
q3	10%	7%	9%
q4	10%	11%	11%
Total	11%	9%	10%

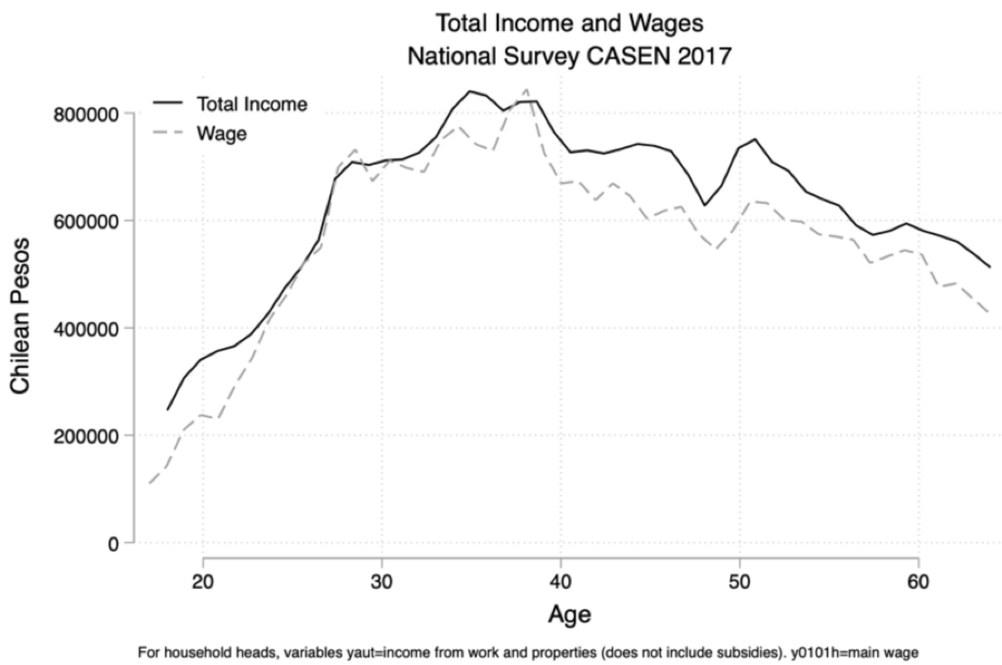
The table bellow shows the NEET for individuals in four income quartiles. The results show a very high proportion of low-income females' NEET (32%) and a low proportion of high-income males (8%). This profile seems different from the administrative data, as we have a low proportion of NEET low-income males, and more high-income males without data.

Figure 14. Not working, in Education or Training

	Male	Female	
q1	20%	32%	26%
q2	12%	28%	20%
q3	17%	31%	25%
q4	8%	27%	16%
Total	13%	27%	20%

Lastly, using the CASEN 2017 it's possible to analyze if the wages of individuals is similar to their total income. The figure bellow shows the wages and total income of individuals and their age. It's possible to see that the wages are a very. good proxy of their income between 25 to 32 years of age.

Figure 15. Missing Information

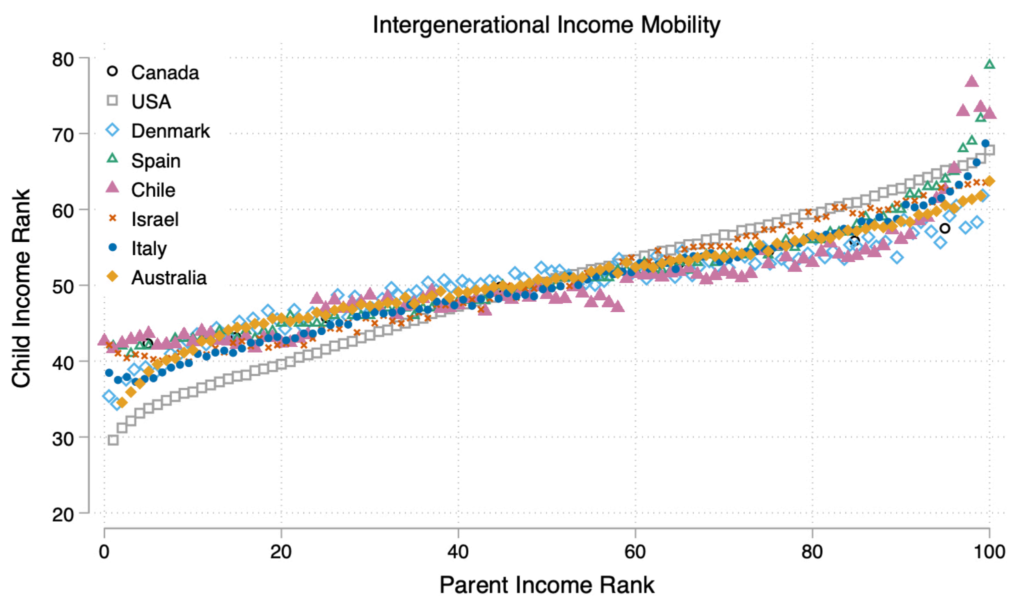


VII. Appendix II

Table 9—Intergenerational Mobility Estimates Using Administrative Data

Results from Other Countries				
Country	IGE	Rank-Rank	Missing Data	Authors
Australia	0.185	0.215	15-20%	Deutscher & Mazumber (2020)
Chile	0.43	0.21	27%	Authors' own work
Italy	0.25	0.25	65%	Acciari et al. (2019)
Israel	0.28	0.251	18.3%	Oren Heller (2017)
Norway	0.194	0.223	4%	Bratber et al. (2017)
Spain		0.235	40%	Costas et al. (2020)
Sweden	.216	0.183	5%	Heindrich (2017)
United States	0.344	0.341	15-50%	Chetty et al. (2014)

Figure 16. Intergenerational Mobility Rank-Rank Comparison



Data from Canada by Corak and Heisz (1999), USA by Chetty et. al. (2014), Denmark by Boserup, Kopczuk, and Kreiner (2013)
Data from Spain by Llaneras, Medina & Costas (2020). Chile by francisco.meneses@duke.edu. In Chile, child wage rank age 27
Israel by Oren Heller (2017). Italy by Acciari, Polo & Violante (2019). Australia by Deutscher and Mazunder (2020)

VIII. Appendix III

A. Areas of Study

Even after graduating from college, low-income students face several challenges. Table 7 shows the areas of study defined by the OECD, and the probability of these students to reach the top 10%. There are areas of study that, even after graduation, provide a very low chance for the student to get to the richest 10%. For low-income students, being an engineer provides over 30% probability of reaching the richest 10%, while there is no possibility if the student studied humanities. The fourth roadblock that students face is to choose the area of study. In Chile, students elect their college major before enrolling in college and have almost no possibilities to change later.

Table 10—Areas of Study of Students, and proportion that reaches Richest 10%

	q1	q2	q3	q4
Agriculture	17%	19%	14%	30%
Sciences	29%	39%	40%	45%
Social Sciences	23%	29%	27%	45%
Education	15%	16%	14%	19%
Humanities	0%	7%	7%	15%
Engineering	31%	36%	39%	56%
Health	23%	27%	32%	40%
Services	12%	12%	16%	20%

Table 11—Areas of Study of Students, and proportion of total graduates

	q1	q2	q3	q4
Agriculture	2%	1%	2%	2%
Sciences	4%	5%	5%	4%
Social Sciences	22%	21%	22%	31%
Education	33%	31%	28%	16%
Humanities	2%	2%	3%	5%
Engineering	13%	14%	15%	18%
Health	20%	22%	22%	22%
Services	4%	3%	3%	2%
Total	100%	100%	100%	100%

The effect on intergenerational mobility of the area of study reinforces the impact of role models. It has been shown that role models affect the area and major of study of students in Chile (Altmejd et al., 2020; Barrios Fernández, 2019). Therefore, role models seem important for students to climb the mobility ladder, as they will help students choose the most profitable career paths.

Table 8 shows the students that reach the top 10 percent, by their parental income and sex. The results show that male students have a 60% probability of getting to the top 10%, while female students have only a 40% probability. However, these probabilities are not homogeneous among all income groups. High-income females compose 45% of the individuals of their income group that reach the top 10%, while for low-income individuals that reach the top, females are only 32%.

Educational Mobility

Moving towards education, Table 9 shows that average years of education for children and their mothers for their original income quartile. The results show that children in all income groups increase their average years of education in 3.6 years or more, with the lowest income group increasing the most 5.5 years of average education. These results would confirm that in Chile there have been important increases in educational investment and mobility, benefiting all income groups.

Table 12—Add caption

	Original Income Quartile			
	q1	q2	q3	q4
Childs' Education	13.4	14.5	15.4	17.2
Maternal Education	7.9	9.4	10.7	13.5
Difference	5.5	5	4.7	3.6

Table 10 shows the matrix of intergenerational educational mobility, comparing maternal education and the education of the adult child at age 26. The matrix is over the categories of education (primary, high school, vocational, college, and graduate). The matrix shows that there is upward educational mobility for the children of mothers with primary, high school, and vocational education. There is a high correlation of educational level for the children of mothers with college and graduate education.

The descriptive results of this subsection start to describe the intergenerational mobility environment of this cohort in Chile. These last results also confirm the stickiness and downward mobility for female students. As the educational level has increased in this generation, there is high upward educational mobility in all groups.

Table 13—Educational Mobility Matrix

	Maternal Education				
Child Education	Primary	High School	Vocational	College	Graduate
Primary	2%	0%	0%	0%	1%
High School	51%	24%	9%	4%	2%
Vocational	30%	33%	22%	11%	7%
College	17%	41%	66%	78%	80%
Graduate	0%	1%	4%	6%	11%

IX. Appendix IV

Table 14—Summary of Main Regression Results

	Equation (1)	Equation (3)
VARIABLES		
Parental Income Rank	0.204***	0.106***
592 Trajectories	no	yes
Constant	0.404***	0.08****
Observations	181,885	181,884
Adj R-squared	0.041	0.242

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