INTERGENERATIONAL PERSISTENCE IN INCOME AND EARNINGS

The case of Chile

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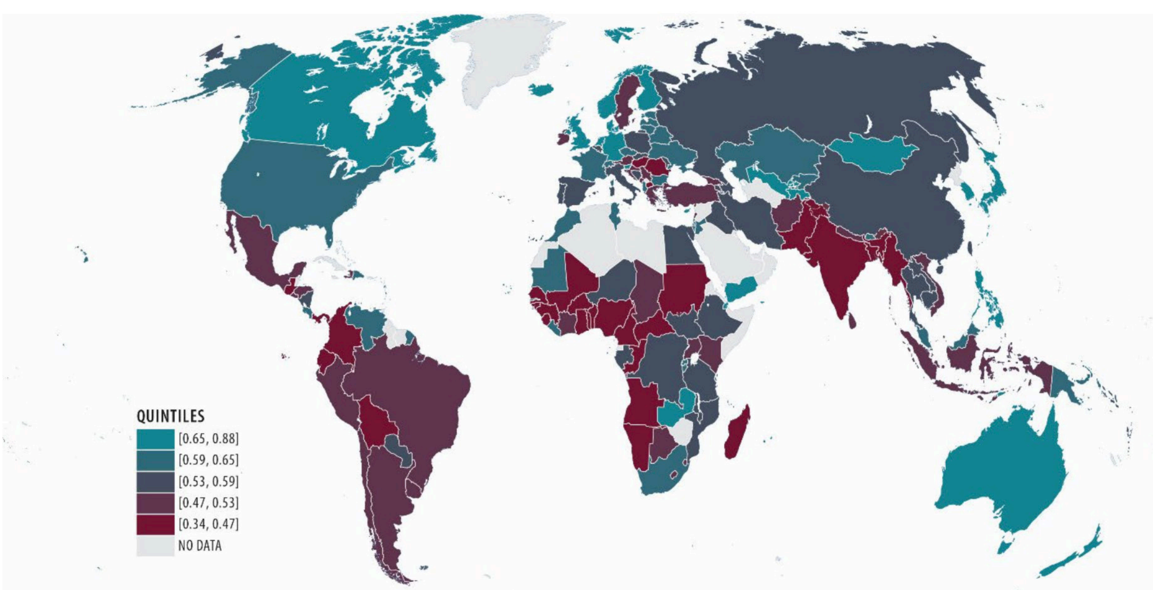
INTRODUCTION

Intergenerational mobility captures the association between parents and their children for a given outcome. Outcomes could include schooling, occupation, socioeconomic classification, income, earnings, health and many others. They map the way in which parents shape and influence their children through different channels, including direct economic resources but also cultural capital, time investments, among many others. In this context, mobility can be interpreted as the opposite of persistence – higher mobility means that parents outcomes have a lower influence on their children's outcomes. In this article we study intergenerational mobility in Chile with a focus on income and earnings.

Measuring intergenerational mobility in income is a data-demanding endeavour. It requires long-term data linking parents and their children, ideally observing both in their prime working years, usually between 30 and 50. As expected, such data is only available for a few countries in the Global North. In the absence of such data, several alternatives have been proposed. One such alternative is the study of the intergenerational transmission of education, commonly measured as the correlation between the years of school of the parents and their children.

The World Bank has pursued this avenue, providing estimates of mobility for 153 countries across the world in their Global Database on Intergenerational Mobility (van der Weide et al., 2021. Figure 1, taken from van der Weide et al., (2021), reports estimates of mobility for individuals born around 1980. We see that Chile ranks in the top quintile in terms of educational mobility, with low intergenerational persistence. Countries with lower mobility are most prevalent in Sub-Saharan Africa, Central America, Eastern Europe and South Asia.

Figure 1: Relative mobility in education around the world (1980s cohort).



Note: The map captures relative mobility for individuals born in the 1980s. Economies are classified according to quintiles of the mobility measure. A higher value indicates greater mobility. Relative mobility is measured as one minus the correlation coefficient between children's and parents years of schooling.

The high level of educational mobility in Chile is partly explained by changes in mandatory schooling laws. In 2003, Chile went from a minimum of 8 years of school to 12 years. Children affected by this change will have up to 4 more years of school, irrespective of their parents educational level. As such, the association between parents and their children is attenuated. This can also be seen when studying absolute mobility, that is the share of children that achieve a higher level of schooling than their parents, as reported in Muñoz (2021), shown in Figure 2. When it comes to educational outcomes, Chile is among the countries with both highest upward mobility and lowest downward mobility. While educational mobility can give us an idea of how schooling improves irrespective of origin, once a certain level of mandatory education has been achieved it tells us little about overall intergenerational patterns.

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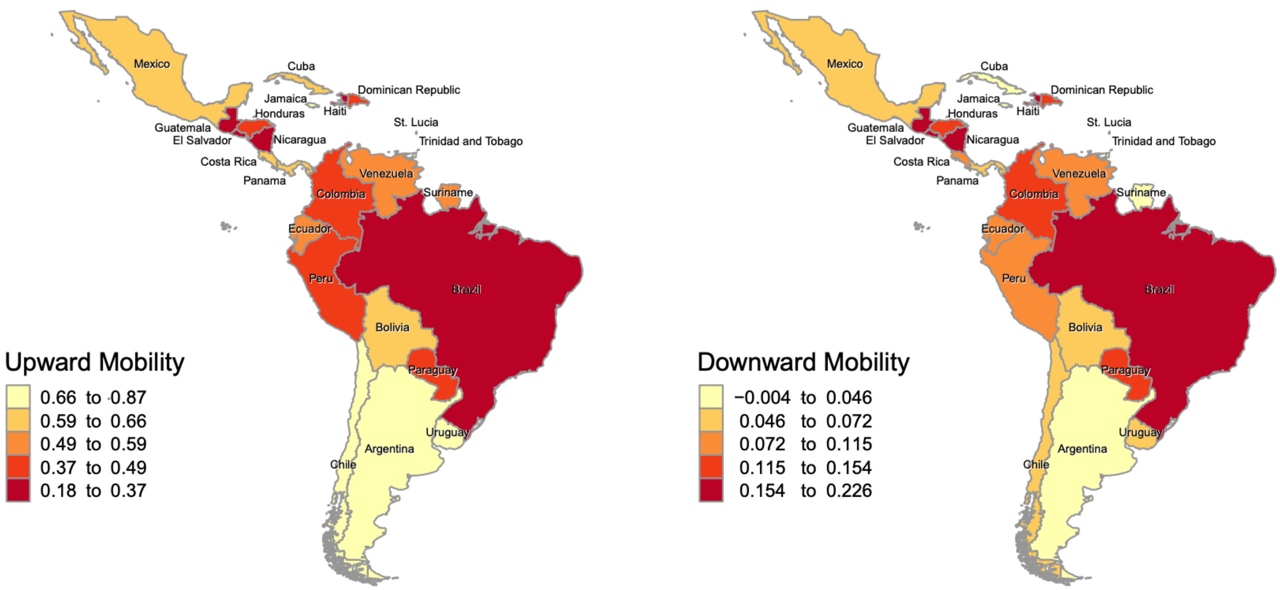


(a) Upward Mobility

(b) Downward mobility

Note: Upward mobility reflects the likelihood that children aged 14–18 whose parents have not completed primary schooling will manage to complete at least primary education. Downward mobility reflects the likelihood that children aged 14–18 whose parents have completed primary schooling or higher will not manage to complete primary education.

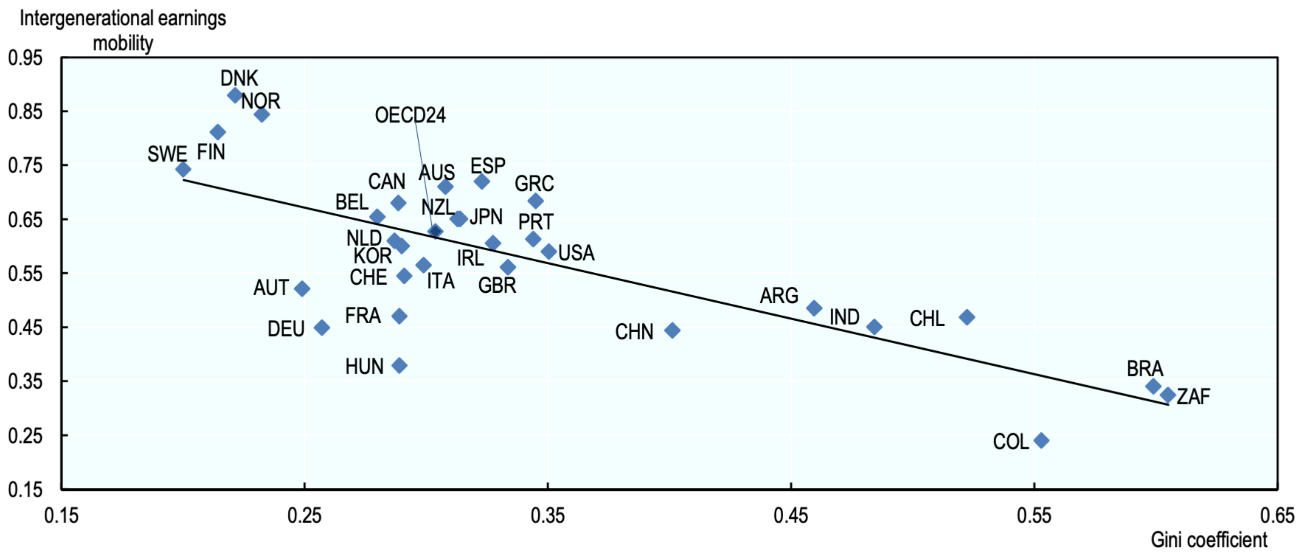
While data is limited, there have also been other studies looking at income persistence. Particularly relevant is the OECD flagship report on social mobility OECD (2018). Among the many ways in which they study mobility, one is to assess the number of generations it takes for a family at the bottom 10% of the income distribution to reach their country's average income, given the current mobility structure. Chile joins Argentina, France and Germany in reporting 6 years, higher than the OECD average (4.5 years) but still above other countries such as China, India and most of the Latin American region. Similarly, Chile shows one of the highest shares of sons with low-earning fathers that end up in the top 25% of the income distribution.

Before concluding anything about intergenerational mobility in Chile we need to consider some distributional aspects. Concretely, what does it mean to receive the country's average income or to be in the top 25% of the income distribution. The Chilean distribution follows a particularly 'flat' structure, with very slight differences in income for the bottom 80% to 90% percent of the population and where major differences arise when looking at the richest 5% (see, e.g., De Rosa et al., 2022). This means that moving across the income distribution in Chile requires less income than in other countries with similar mobility. Indeed, using data from the World Income Distribution dataset (Milanovic, 2012) we see that moving from the bottom 10% to the average in Chile requires around 6.5 thousand additional dollars (PPP) versus 11.5 for Germany and 12.5 for France. Based on this pattern of high mobility across most of the income distribution but the very top, Torche (2005) refers to Chile as an 'unequal but fluid' country.

The second approach to measuring mobility in the presence of subpar data relies on statistical methods to predict parental income. The idea being that parental income, while not directly reported in the survey, can be proxied by a series of variables which typically include information on the parents such as their educational level or their occupation. This literature relies on two-stage methods where income is estimated for an older survey (the parents' generation) and then predicted for the current survey (the children generation) using a set of variables that can be found in both datasets. These estimations rely on instrumental variables and more recently on machine learning methods to obtain a prediction (Bloise et al., 2021). The problem of these methods, however, is that they tend to overestimate the extent of persistence, resulting in lower levels of mobility (Jerrim et al., 2016). By looking at the correlation between (predicted) parental income and the income of their children, these approaches estimate what it is typically called an intergenerational elasticity for income.

The OECD has relied on these methods to provide estimates of the intergenerational elasticity across countries. In their same flagship report (OECD, 2018), they find an elasticity of 0.53 for Chile, similar to that of Argentina and France, and higher than that of the Nordic countries (at around 0.2) or the UK and the USA (at around 0.4). Figure 3 presents these estimates together with the level of inequality of each country, showing a negative association which has come to be known as the 'Great Gatsby Curve' (first presented in Corak (2013) and coined by economist Alan Krueger). This association reinforces that idea that intergenerational persistence and income inequality are two sides of the same coin, and they are typically associated though multiple channels, as highlighted by Durlauf and Seshadri (2018). Including income inequality gives us an extra layer of complexity when putting intergenerational persistence in context. Indeed, we find that Chile resides in a low mobility and high inequality area, together with countries such as Argentina and India.

Figure 3: In most countries, earnings mobility across generations is higher when income inequality



Note: Earnings mobility is proxied by 1 minus intrgrational earnings elasticity of fathers with sons. Gini coefficients refer to the mid-1980s/early 1990s.

Source: Chapter 4
Fuente: OECD (2018)

While part of a different literature, the concept of inequality of opportunity follows closely that of intergenerational persistence. A measure of inequality of opportunity assesses the extent to which a given distribution (income, earnings, health, education, etc.) can be explained by factors over which we have no control -typically referred to as circumstances. Moreover, these two concepts are not only conceptually similar but also operationally, as they can be shown to stem from the same starting point (Carranza, 2023). The choice of circumstances is a normative endeavour, which is why inequality of opportunity can be interpreted as a measure of unfair inequality. Indeed, the higher the share of inequality accounted for by circumstances, the higher the level of inequality of opportunity.

Brunori et al. (2023) provide an exhaustive overview of inequality of opportunity in Latin America. Using state-of-the-art methods, they find that the share of income inequality attributed to circumstances is high in the region, much higher than Europe, for example, accounting for around half of total inequality. Among the countries for which there is data, they find that Chile is somewhere in the middle, with 52% of total inequality accounted for by circumstances. Higher than Argentina, Ecuador and Guatemala (at around 45%), but lower than Brazil, Peru and Panama (at around 55%). In terms of specific circumstances, Chile is among the countries where parental education matters the most and where ethnicity matters the least.

In addition, the Development Bank of Latin America (CAF) has recently released a report on inherited inequalities across the region (CAF, 2022). In it, they highlight three factors as the main drivers of intergenerational persistence: human capital, labour market opportunities and wealth accumulation. Economic recessions reinforce the disequalizing of these factors and, conversely, these factors buffer the impact of these shocks, further reinforcing inequalities. The report also praises the increase of secondary and tertiary schooling in Chile, while also noting important socioeconomic gaps that have remained. These include the lack of upwards mobility among minority ethnic groups and the important socioeconomic gradients in standardises test scores, university attendance and labour market participation, particularly among women.

Together, these findings show that Chile is an interesting case for the study of intergenerational mobility. At first glance, it appears to be a very mobile country but when taking its level of inequality – and more generally, the shape of the income distribution – into account we see that this is not necessarily the case. Indeed, educational mobility plays a big role in shaping persistence from one generation to the next, and where existing inequalities are heavily inherited. This article presents an overview of income mobility in Chile, incorporating both primary and secondary data sources to explore intergenerational persistence across different groups and over time.

We begin with a review of existing estimates of mobility and what can they tell us about mobility patterns in the country. We complement this review with an estimate of our own, but due to the complex nature of our estimation approach, we begin with a more straightforward descriptive analysis. First, we look into average income by the level of education of the respondent's parents and how it has varied over time. We focus on parental education as it amongst the main predictors of current inequalities and therefore a good first approximation at the issue of the intergenerational transmission of advantages and disadvantages.

Second, we explore in detail the role of certain demographic and socioeconomic characteristics in shaping intergenerational persistence. As a first approximation we look into the role of parental education, and how its importance varies across certain demographic and socioeconomic groups. Our final contribution is to estimate the intergenerational elasticity of income for Chile that while more complicated methodologically, provides a unique summary indicator to assess persistence. We finish by studying how the intergenerational elasticity varies across different groups.

Existing estimates of intergenerational mobility in Chile

The current section presents an overview of the literature on intergenerational mobility in Chile. It includes an up-to-date review of existing estimates, current data sources and methods, and what can they tell us about the intergenerational transmission of inequality. Because these estimates rely on a plethora of approaches they cannot be directly compared. However, taken together, they provide a detailed picture of the different dimensions of intergenerational mobility in income and earnings.

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Nuñez and Miranda (2010, 2011) were among the first to study this phenomenon in the Chilean context. In their first study they found a range of estimates from 0.57 to 0.74 percentage points for men group between 25-40 years of age. When looking at men aged 31 to 40, that range compresses to 0.63-0.76. The second paper relies on data from the Employment and Unemployment Survey of Greater Santiago (Encuesta de Empleo y Desempleo del Gran Santiago in Spanish), where they find estimates ranging from 0.52 to 0.54. Being the first estimates of the intergenerational elasticity for Chile, these numbers have been used for most cross-country comparisons, such as the Global Database on Intergenerational Mobility (GDIM). The authors use Two-Sample Two-Stage Least Squares (TSTSLS) to predict parental income and then estimate the intergenerational elasticity. This approach over-estimates the level of persistence, particularly when the number of variables used to predict parental income is small (Jerrim et al., 2016). In addition, these estimations also suffer from a downward bias as children at observed at an early age, such that 'prime age' earnings have not been realised yet.

Around the same time, Celhay et al. (2010) used longitudinal data to provide estimates of intergenerational mobility in income. Through the long-running nature of this data they are able to observe both parents and children at around age 20 and 45. They compare their findings to other estimates in the region, showing that there is an intergenerational income elasticity of 0.51 for the full sample. The also highlight differences across gender, with an intergenerational income elasticity of 0.59 for men and 0.43 for women. As with many studies relying on household surveys, they can only capture observed (i.e., 'short-term') income, thus suffering from life-cycle bias, which is somewhat addressed by controlling for the age of both parents and children.

More recently, Gaentzsch and Zapata (2018) used an imputation method loosely based on TSTSLS to estimate the intergenerational elasticity[3] of income for both Chile and Peru. Instead of relying on retrospective data on the parents, they use individual data on education and other factors to predict the income of the parents. For the case of Chile, they estimate a coefficient for market income of 0.66 and 0.76 for disposable income. They also estimate measures educational mobility. While the estimate for absolute mobility is 0.43 in Chile and 0.49 in Peru, their measure of relative educational mobility equals 0.54 in Chile and 0.45 in Peru. They interpret this reversal by discussing how the dispersion of educational attainment has decreased in the children's generation compared to the parents' generation in Chile, while the opposite has happened in Peru.

Lastly, Cortes-Orihuela et al. (2022) rely on administrative records for the purpose of

3 We discuss the TSTSLS approach in the Appendix.

studying mobility in earnings. They use the unemployment insurance (UI) database, which they combine with records from the registry office (Registro Civil in Spanish) to link parents and children together, both observed between 2002 and 2018. Using the mean labour income of both parents, therefore excluding financial income, they find estimates ranging from 0.28 to 0.31 for the intergenerational earnings elasticity. Moreover, they find that women exhibit higher persistence in earnings than men. Indeed, the mother-daughter association is 0.07 percentage points higher than the father-son case.

While allowing for an extremely detailed description of mobility dynamics across the earnings distribution, their data suffers from some caveats. First, this dataset only includes the earnings of those formally employed which amount to around 70% of the workforce. Second, the UI system and therefore the database was first available in 2002. All new contracts were automatically signed to the system while existent contracts could opt-in. The result was that the UI database over-represented short-term contracts relative to open-ended ones up until around 2009 (Sehnbruch et al., 2019). Moreover, this restriction reduces the number of feasible parent-children matches that this dataset can attain. As such, their results highlight the issues underlying the use of administrative records for this type of analysis and – in the case of Chile – should be interpreted as a measure of formal labour market dynamics.

Parental education and income differences

Assessing intergenerational mobility quantitatively poses a significant challenge due to limited access to data. Ideally, researchers would use long-term data panels that can observe both parents and their children, observing both at around age 40. However, this is rarely feasible outside of a few countries in the Global North. An alternative approach to longitudinal data is to use retrospective questions about parents, usually revolving around respondents' teenage years. In this section we employ these variables, particularly information on parental education, to explore income dynamics and how intergenerational persistence shapes them.

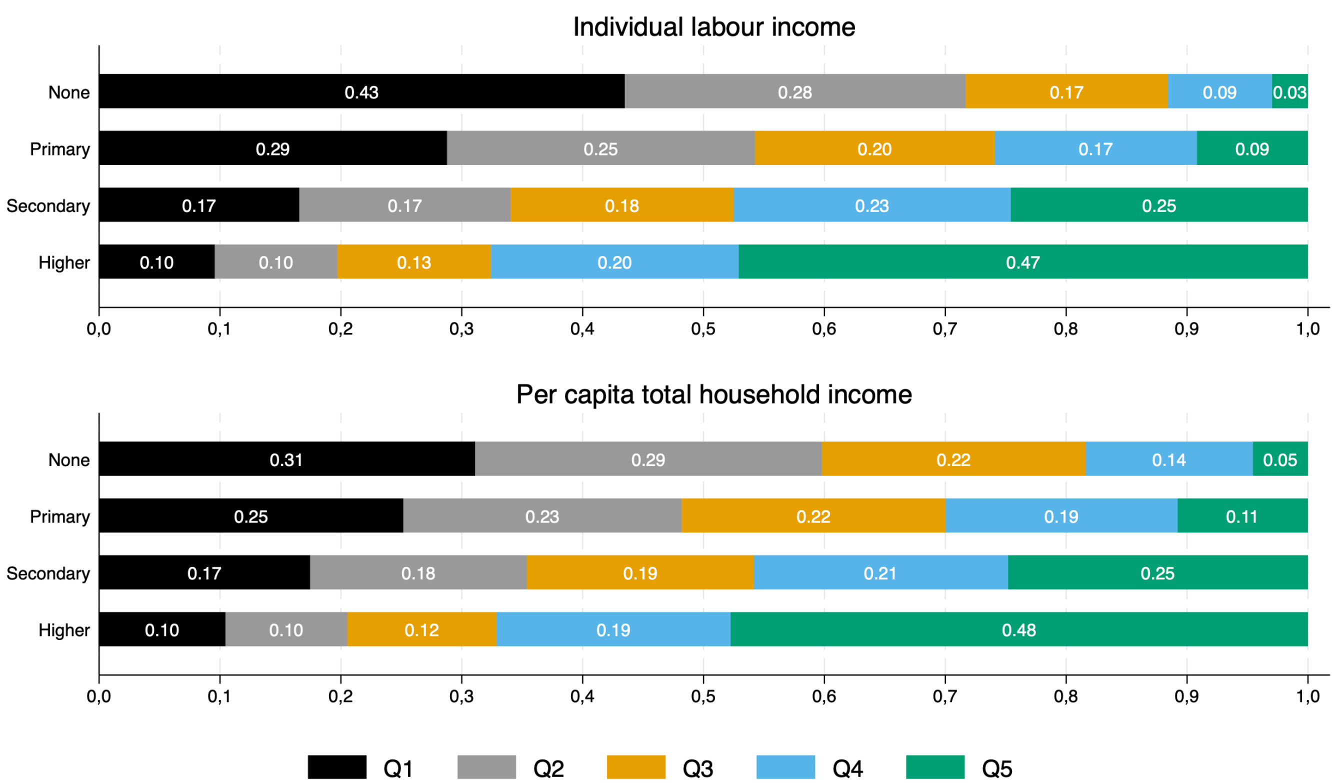
To accomplish this, we use data from the Chilean Encuesta de Caracterización Socioeconómica Nacional (CASEN), which is a nationally representative household survey carried out every 2 or 3 years since 1990. We employ parental education as reported in CASEN in two ways. Firstly, we use it as our main classification variable to distinguish between-group differences over time and across specific groups. We use parental education as one of many predictors of parental income, therefore providing estimates of intergenerational elasticity of income, that is, the association between the income of the parents and that of their offspring. These analyses provide an overview of how intergenerational mobility varies across multiple dimensions in Chile, including whether persistence has grown and which groups exhibit the strongest persistence.

The role of parental schooling

We begin by describing the relationship between income and the education of the respondent's parents. We do this for two different definitions of income, individual labour income (i.e., earnings from work) and household per capita income. Household income is the standard measure when studying inequality or poverty. However, by aggregating all incomes in the household it hides any within-household disparities, attenuating, for example, the role of gender and age differences. For this reason, our second measure concerns individual earnings (i.e., wages) – this is not a measure of available resources but rather of the role of labour markets in shaping income inequalities. These two measures complement each other and provide a broad overview of the role of parental education in socioeconomic outcomes. We begin by splitting the sample into five equal size groups called quintiles, and assessing the incidence of these groups by the level of parental education.

Figure 4 shows stark differences in income based on parental education. Among those whose parents had no schooling, we see that 43% of them come from the bottom quintile of individual earnings (31% for per capita income). At the other extreme, looking at those whose parents had higher education, we see that more than 45% of them come from the top 20% of the population. This trend holds across all levels of parental schooling and for both earnings and income. For those

Figure 4: Individual labour and per capital household income quintile by educational level



whose parents had primary and secondary degrees we find a relatively uniform distribution – close to that of the population as a whole. In part this is due to these groups representing the largest share of the population. However, we do see some departures at the bottom and top of the distribution: Low-income respondents are more common among those with primary-educated parents while high-income respondents are slightly more prevalent for those with secondary-educated parents. Overall, we find that the data suggests a strong socioeconomic gradient based on the level of education held by the respondent's parents – suggesting a strong degree of intergenerational persistence.

We find that household income attenuates the socioeconomic gradient present in wages, particularly at the bottom of the distribution. The bottom quintile of income is overrepresented among those whose parents had no schooling – they account for 43% of that group when ranking respondents based on their individual earnings but only for 31% when ranked based on household income. This means that other sources of income manage to attenuate these differences. These sources could include non-labour income, particularly social transfers but also income from the remaining members of the household. However, we find that this attenuation of the socioeconomic gradient does not happen at the top – almost half of those whose parents had a higher education are in the top 20% of the population, for both earnings and income. We can therefore attribute this to social spending, which it is heavily directed towards the bottom quintile while having no impact on high-income families. In other words, we find that cash-benefits appears to attenuate the importance of having parents with no schooling on labour market outcomes, but it has no impact on those with highly-educated parents, where labour market inequalities translate directly to household income inequalities.

Parental education and income differences

Income and earnings dynamics over time

Using the CASEN survey we can also assess how these socioeconomic gradients have changed over time, from 2006 to 2017. We categorize individuals into five groups depending on the highest level of education achieved by either parent. These groups consist of parents with no formal education or less than primary education, those who completed primary education, those who completed secondary education, those with a vocational degree, and those with a tertiary or university degree. Consistent with the previous section, we focus on two measures of income: per capita household disposable income and individual earnings. We look at the average income at each survey year and for each of the five parental education groups.

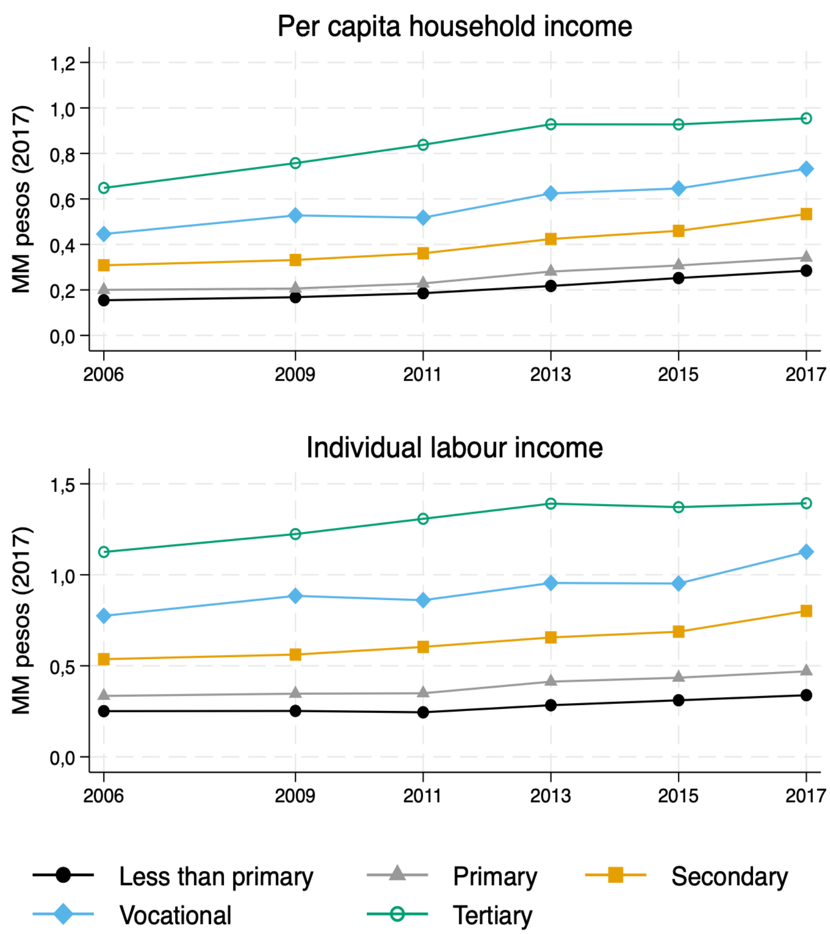
Figure 5 shows the evolution of both income measures over time, both reported in inflation-adjusted 2017 Chilean pesos.[4] We find that average incomes are ranked in the way one would expect – respondents whose parents had primary or less than primary show the lowest levels while those whose parents had tertiary education have the highest. Those whose parents had either secondary or vocational education lie somewhere in the middle. Over time, we see that all groups follow a similar trend of positive income growth, except for those with higher-educated parents starting from 2013 – although their lower growth rates are not enough for the remaining groups to catch up.

The differences between these groups can be significant, with up to 750 thousand pesos (approximately 1,150 USD) in per capita household income and well above 1 million pesos (approximately 1,500 USD) in labour market earnings. Differences among those with parents with

4 CASEN changed its income methodology in 2015. Up until then all income measures were rescaled to match the respective component as reported in the National Accounts. This created a break between the 2015 and 2017 waves, which we avoid by using the unadjusted series for the entire period.

primary or less than primary, and to a lesser degree those with parents with secondary education, have remained relatively small. It is between those three categories and those with parents with tertiary education where differences are the largest, suggesting the presence of a group at the top that differs systematically from the rest

Figure 5: Evolution of per capita household income and individual labour income over time (inflation-adjusted 2017



Parental education as a determinant of income inequality

An obvious question that arises from the previous section is the degree to which between-group differences matter in explaining total income inequality. The previous sections have given us some insights on this by focusing on averages and quintiles, but standard inequality decomposition methods can help us explore this issue in greater detail. In this section we assess the extent to which total income inequality is explained by differences in levels of parental schooling . We rely on the Gini coefficient to assess income inequality and its decomposition. While the Gini does not allow for an absolute decomposition into between and within differences, the fact that this is a well-established inequality measure will help us in conveying our message and interpreting our findings (see the Appendix for details on this decomposition approach and the use of other inequality indexes).

The general idea behind decomposition an inequality estimate is to compare the extent to which differences in inequality stem from between or within-group differences. In our case, groups are defined by the highest level of education of either parent. Between-group inequality can be therefore interpreted as the level of inequality if everyone in a given group has the same income, so that the only differences that arise are due to being in different groups. One useful aspect of this approach compared to the previous ones is that it allow us to use the full set of educational categories for the parents instead of having them grouped, allowing us to account for the full diversity of educational backgrounds of the parents.[5]

We extend our analysis by providing further decompositions for specific categories. These categories include gender, age, identifying as part of the indigenous population, region, occupation, industry, the European socioeconomic classification of occupations, schooling, poverty status and income decile. We do so by estimating the share of inequality due to between-group differences for each of these categories. By contrasting the decomposition across these categories we can assess the importance of parental education relative to the general population. Intuitively, the larger the share of total inequality accounted for by between-group differences, the larger the incidence of parental education in explaining income of the current generation.

Table 1 shows the between-group share of per capita household income for each category. To give some insight into the characteristic of each category, we also include median and average income, as well as the mean to median ratio as a proxy measure of within-group inequality. We also include a measure of relative income (mean income of that group divided by mean income) and the population share of that given category. The last row, which describes these statistics for the full sample, shows a median per capita income of almost 300,000 pesos (456 USD) and an average of 466,000 pesos (718 USD), equivalent to an average 60% higher than the median. Looking at the full population, parental education accounts for 46% of all income inequality. In other words, if all respondents whose parents had the same level of education were assigned the same income, equal to the average of their group, income inequality would be equal to 46% of the current level.

Age, gender and ethnicity

Looking at gender, we see that parental schooling is slightly more important among men, but that difference is small. Across age groups, we see that is importance is more salient among those in prime working age, 35 to 44, and the over 75. These are also the two age groups with the higher levels of inequality, as measured with the mean to median ratio. Working age individuals and pensioners show both the highest dispersion of income and the largest importance of parental education – a pattern we will see throughout this section. Across indigenous groups, we see that between-group inequality is larger among the indigenous non-Mapuche group rather than for the Mapuche, but these are both relatively small groups in the population.

We find that these three categories show relatively small differences. In other words, parental education does not play a systematically different role across categories. This is partly due to the nature of our income variable, as household income tends to average out differences due to individual characteristics such as age or gender, as the income of all working household members is added up. This is particularly true in the case of heterosexual couples, where the income of each partner is included and divided equally among the two. In such a case, difference in gender tend to capture differences in household composition, as we would be comparing households with two partners relative to, say, household with a single female parent. As such, given our focus on household income, we expect that differences by gender to be relatively small.

The largest differences we see are between the group that identifies as Mapuche (and to a lesser extent, all other

5 The full set of parental educational categories includes: Not attending school, primary, secondary and vocational school for both for the 'old' (i.e., pre-1965) and 'new' systems, tertiary degree (either vocational or university) and a postgraduate degree.

indigenous groups) and the non-indigenous population. Parental education plays a much smaller role in shaping income inequalities within the Mapuche ethnic group, 37% of all inequality relative to 46% for the non-indigenous population. While this could be construed as a measure of higher mobility, it actually represents the fact that parental education is less diverse among the Mapuche. 24% of the Mapuche respondents had parents with no formal education, compared to 14% in the non-indigenous population. On the other hand, 11% of the non-indigenous population has parents with a university degree versus 5% for the Mapuche. Moreover, we show that the Mapuche have average incomes 30% below that of the rest of the population. What these differences say is that parental education plays a limited role in shaping current outcomes within indigenous populations in Chile, partly due to a combination of low parental education and low incomes. However, differences between indigenous populations and the rest of the population are considerable.

Geographical differences

We can also look at differences across region of residence. The role of parental schooling is highest among the residents of the Metropolitan region, the most populous region including over 40% of our sample, accounting for half of all income inequality. The Metropolitan region is closely followed by residents of the Araucanía and Los Lagos regions, two of the poorest regions, where the indigenous population is highest and that jointly account for 11% of our sample. On the other extreme, parental schooling has little importance in the extreme regions at the very north and south of the country, where it accounts for around 25% of overall inequality.

The fact that parental education plays an important role in shaping income inequalities in the Metropolitan region relates to its heterogeneity. It is the most populous region and the one with the largest dispersions of income – indeed, it shows slightly higher income inequality than the country as a whole. As such, we see that here parental education explains a substantial part of those differences. In other words, it is in the Metropolitan Region where intergenerational persistence is the highest, at least when measured in this way. If we were to remove all other differences in income, keeping only those due to different parental education, we would see that the Metropolitan Region would have the largest level of inequality by far – not only because inequality is already higher, but also because parental education plays a larger role.

The next two regions where parental education plays a large role are those with a large share of the indigenous population. In La Araucanía region 28% of the population identifies as Mapuche, while 22% do so in Los Lagos region, relative to 7% for the country as a whole. Together with our previous finding that parental education plays a limited role in within-Mapuche inequality we can draw an interesting conclusion. Once we expand our group definition to the region as a whole, rather than the Mapuche group only, we find that parental education now plays a crucial role. This means that within those two regions, and once we consider both the indigenous and non-indigenous population that reside in it, we find considerable intergenerational persistence. Differences in parental education on inequality matter when assessing differences between the indigenous and non-indigenous populations, rather than when studying indigenous populations on their own.

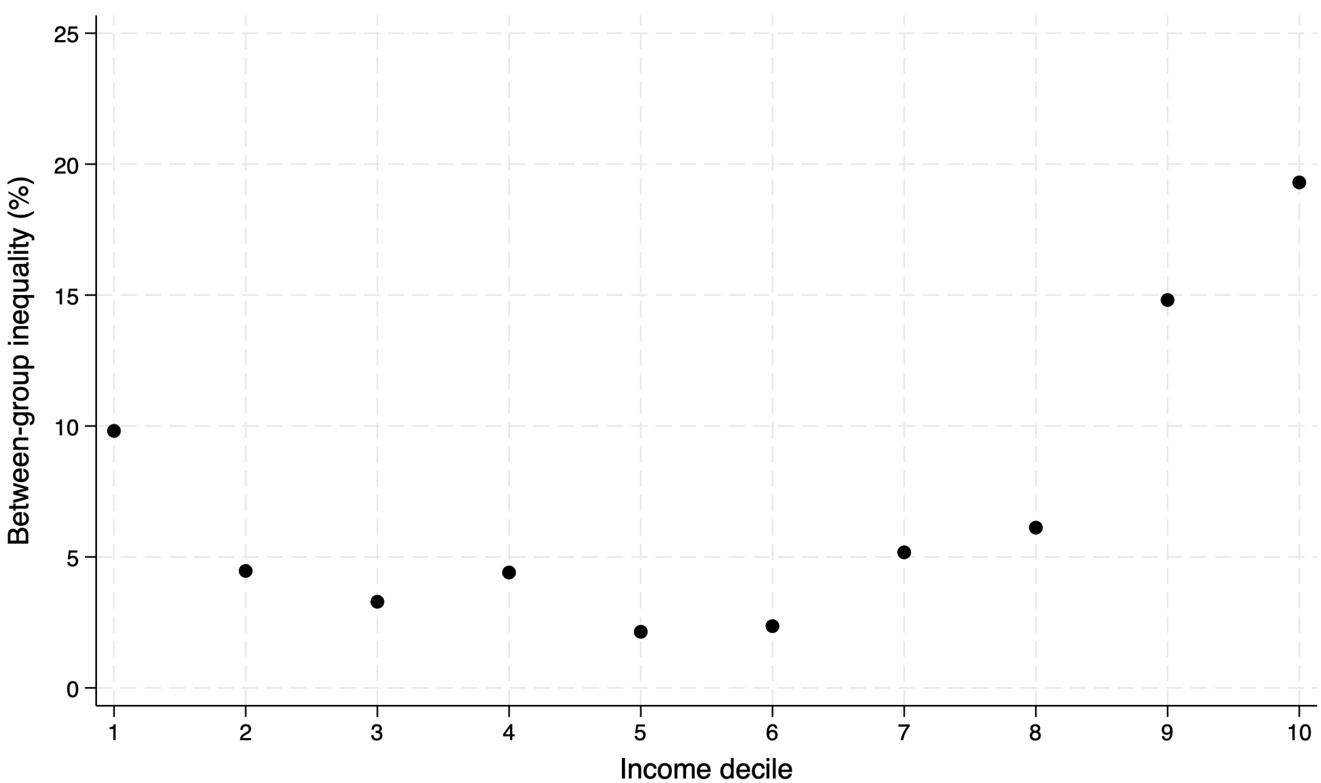
Lastly, we find that parental education matters the lest for the most extreme regions of the country. Interestingly, this is not due to their level of income, as the northernmost regions have average incomes 10% to 20% below the national average while the southernmost region has incomes 30% above. These are, however, regions with very small populations, each accounting for around 1% of the national total. Moreover, these are regions with a relatively low incidence of low-educated parents, particularly those without no education, with shares of 7% to 9% relative to 14% for the national population. These findings also point to a composition effect, where low income workers move out in search of higher wages in other regions.

Education, occupation and industry

Focusing on education allow us to explore its role as a mediator – that is, whether parental education acts a reinforcer of existing inequalities or not. We see a clear cleavage between those with an incomplete university degree or higher and those without one. For the former group we find that parental education plays a relatively important role, accounting for 20% to 35% of all inequality. For those without a university degree we find that parental education plays a limited role, accounting for 6% to 17% of all income inequality. Among those with higher levels of education we find that parental education matters the most, as the potential gains from them are much more important than those with lower levels of education.

From an economic perspective, we can focus on the working force to explore differences across industry as well as occupations. Industries are organised through the ISCO code while occupations are grouped using the European Socio Economic Classification (ESEC) that also accounts for employment status, managerial position and size of the company. Among occupations,

Figure 6: Between-group inequality per capita household income decile Chilean pesos)



The presence of high persistence at the top is consistent with existing findings for the US (Palomino et al., 2018). Whether it is education, occupation or income we find that parental education plays a larger role in shaping the outcomes of those at the top of these categorizations. While this might seem related with average levels, this is not necessarily the case across all categorizations. Regions, for example, show a very limited association between average incomes and persistence. At least when grouped by individual characteristics we see that intergenerational persistence and income are positively associated.

However, our findings do suggest a strong association between the level of inequality and the relative importance of parental education in shaping that inequality. The higher the level of inequality on a given group, the larger the scope for differences to be driven by ascriptive factors such as the education of your parents. This is particularly true in the fishing, real state and health services industries, among working aged individuals (25 to 44) and in the Metropolitan region of Santiago, all categories where parental education accounts for more than half of all inequality. On the other hand, dispersion is the lowest among domestic service workers and those with low levels of education – all categories where parental education accounts for less than 20% of total inequality. This positive association between inequality and intergenerational persistence is consistent with the idea that social mobility and inequality are two sides of the same coin, an idea perhaps best document by the Great Gatsby Curve in Corak (2013).

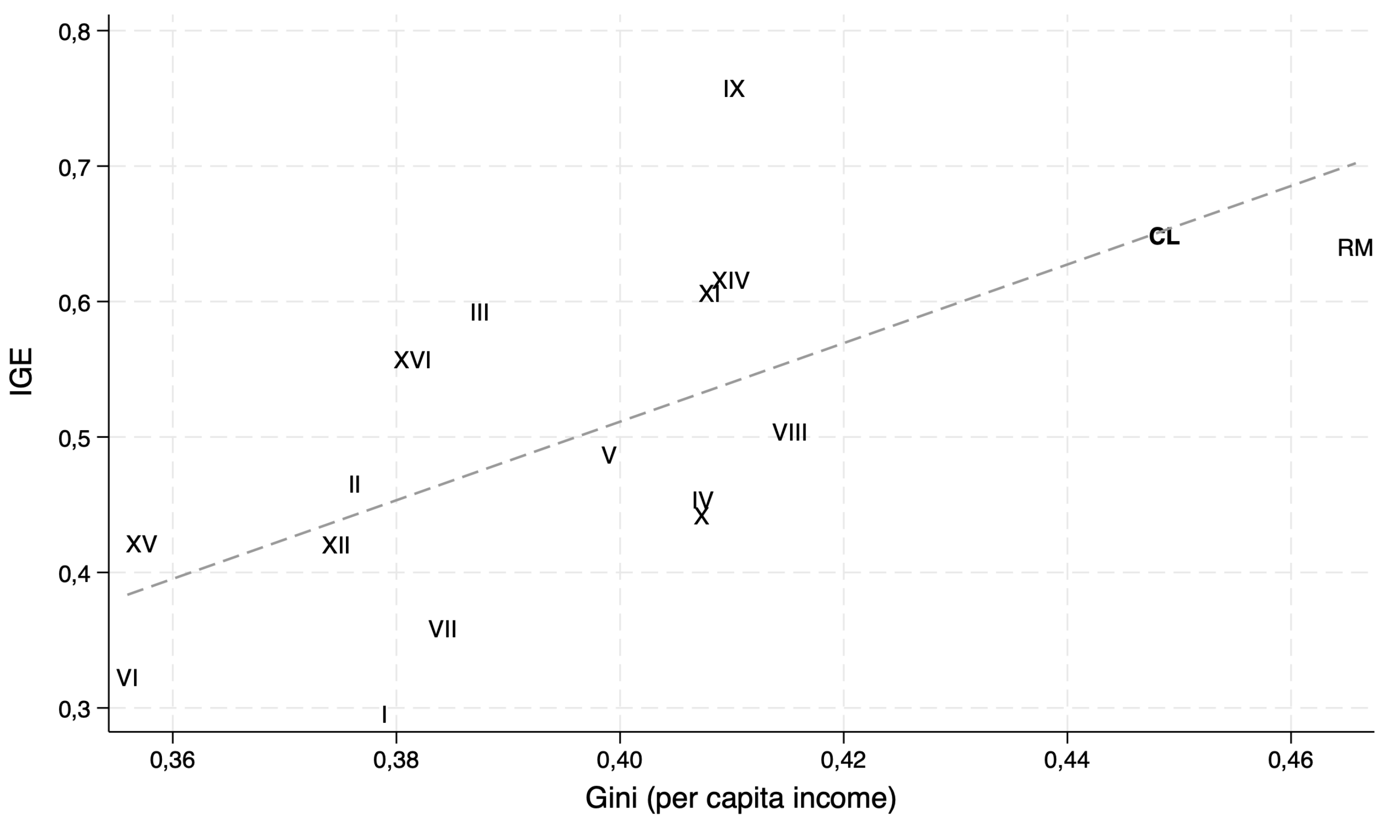
The intergenerational elasticity of income

In this section we explore the association between inequality and persistence in greater detail. We do so by estimating a summary measure of intergenerational persistence, namely the Intergenerational Elasticity or IGE for income. This is a measure of the association between parental income and that of their children, measured in terms of percentage changes. That is, an IGE of 0.6 means that for a one-percent increase in parental income we see that the income of the children should increase, on average, 0.6 percentage points. We provide estimates of the IGE using a prediction technique called Two-Sample Two-Stage Least Squares or TSTSLS (see more details of the estimation approach in the Appendix).Table 2 shows three estimations for the IGE. The first column is an unconditional association between parent and children income, showing an IGE of 0.59. However, as previous studies have shown, we know such an estimation suffers from a series of biases, particularly life cycle bias – the fact that we are not observing incomes at 'prime' working age. The second column accounts for that by controlling for an age polynomial, while the third column interacts parental income with each age polynomial. These are two ways in which we can account for life cycle bias as shown by Lee and Solon (2009). Irrespective of the estimation approach, we see that the IGE ranges from 0.59 to 0.65. This estimation is consistent with previous studies, such as Celhay et al. (2010) , Gaentzsch and Zapata (2018) or Nuñez and Miranda (2010), and it represents a considerable level of persistence, higher than estimates for Europe, the US, or China (Corak, 2013; Fan et al., 2021).

One of the advantages of using the IGE is that it provides a single number to represent the intergenerational persistence between parents and their children. We can use this number to explore the association between intergenerational persistence and overall income inequality. The idea being that higher inequality restraints mobility by making it harder to move along the income distribution, thus making the 'starting point' much more relevant and resulting in higher persistence. Conversely, higher persistence means that inequality in one generation is more likely to shape inequality in the next generation. We can therefore see a two-way link between the two such that higher inequality should be associated with higher persistence.

We explore this idea in Figure 8 by plotting income inequality and the IGE. We do so for each of the 16 regions of Chile together with the national average (labelled as 'CL'). As expected, we find a positive association between the two, with a correlation of 0.66 or a statistically significant regression coefficient of 2.9. This is means that an increase of 1 point of the Gini is associated with an increase of almost 3 percentage points of the IGE. This is a considerable association, close to that found in the original study of Corak (2013) for a series of high-income countries.

Figure 7: Relationship between IGE and current inequality by region

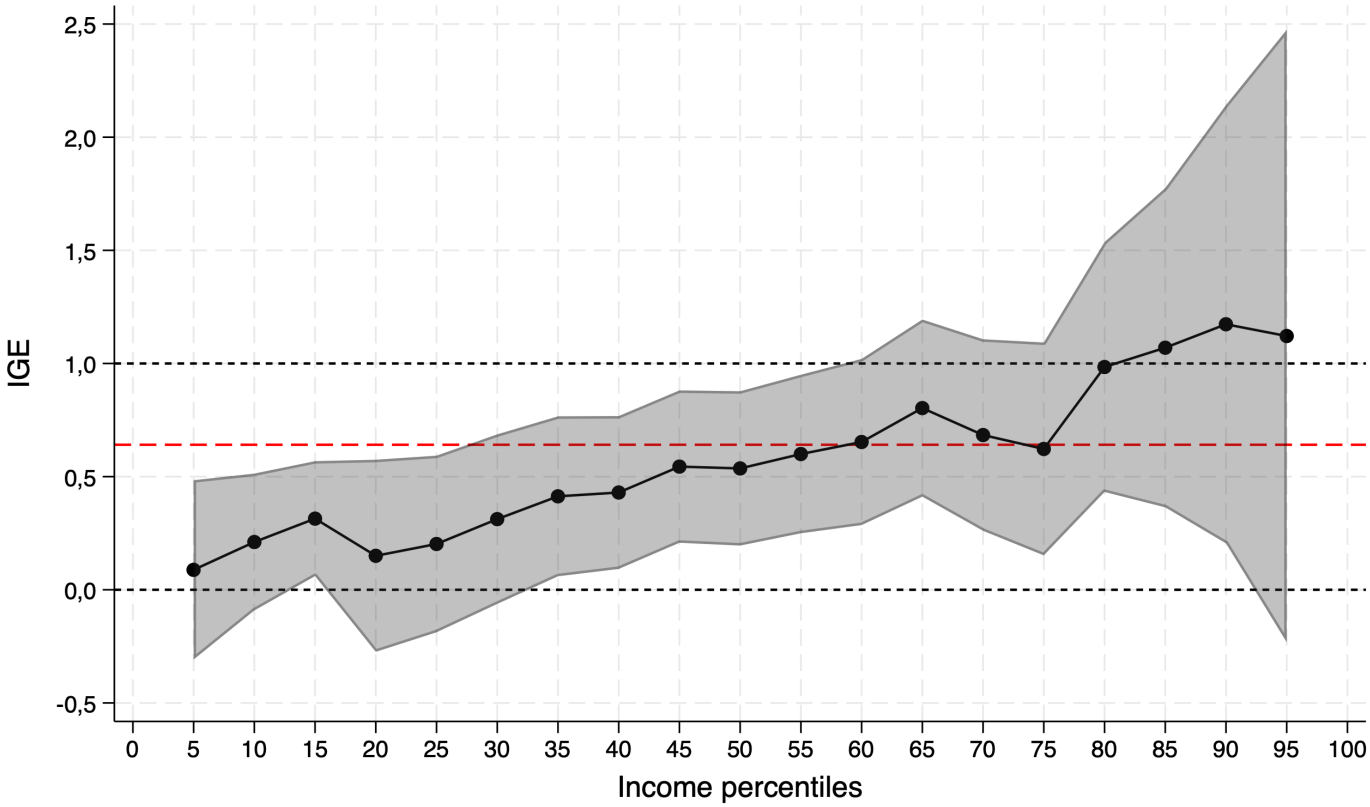


The use of a single estimator such as the IGE allow us to further explore the association between parents and children's outcomes. One way to do so is by going beyond the mean and exploring different quantiles of the income distribution of the children. Recent approaches allow such an analysis and have been applied by Palomino et al. (2018) for the US, among others. We use their approach to assess how intergenerational persistence varies depending on the position of the children in the income distribution.[6]

Figure 8 shows the intergenerational persistence of income at different percentiles of the income distribution. These coefficients represent how parental income influences the income of their children based on where in the income distribution these children are. For reference, we report the average IGE estimate as a

5 The specific technique is called RIF regression, which allows for the estimation of regressions over unconditional quantiles rather than the average as one would in a standard linear regression (see Rios-Avila, 2020, for further details on this approach). While this approach can be applied to our case, it is important to consider its limitations. We use a considerably smaller sample than that of Palomino et al. (2018) who pool several years of data. Moreover, our measure of parental income is a prediction based on a set of observables whereas theirs is the actual income of the parent, reported by the parents themselves 30 years ago. Finally, they use a measure of permanent income averaging several years of data while we rely on a single-year measure. As such, this analysis should be considered a rough approximation to further explore an issue discussed in a previous section.

Figure 8: IGE across the income distribution



The first see we see is that the IGE increases as income increases. Individuals at the bottom of the income distribution show almost no intergenerational persistence – indeed, we see almost no statistically significant coefficient for the first three deciles. This means that for the bottom third of the population the income of their parents has little to no influence. As we move up the income distribution we see evidence of intergenerational persistence, with those towards the middle of the distribution showing levels of persistence very close to the national average. These findings suggest that for a considerable share of the population there seems to be relatively low levels of persistence. This is consistent with the 'unequal but fluid' classification of Torche (2005).

When looking at the top 20% we find that persistence increases considerably, with point estimates well over 1. An IGE above one represents a particularly high level of persistence, such that those at the top are likely to stay there over multiple generations. However, the confidence intervals do not allow us to say much – indeed, the confidence interval for the top 5% is not statistically significant. While the point estimates are extremely noisy to say anything concrete, we can say that intergenerational persistence is negligible for those at the bottom and very strong for those at the top.

These findings are consistent with the discussion in the previous section. Those in top positions, whether in terms of education, occupation or, as in this case, income, show consistently higher levels of intergenerational persistence. All of these findings suggest the presence of 'glass ceilings' that allow those at the top to remain at the top, together with limited evidence for 'sticky floors', as the those at the middle and bottom see a higher degree of mobility. This distinction is particularly relevant if we consider that the income distribution is quite steep at the top. Table 1 shows that the 9th percentile has average incomes that are 60% higher than the average, while the top 10% has average incomes that are almost four times larger. Moreover, the top 10% shows a higher level of inequality, meaning that these differences would be even steeper if we were to look at the top 1%. The presence of higher inequality within the top means that ascriptive characteristics can and do play a bigger role in those groups, further reinforcing inequality across generations.

CONCLUSIONS

What can we say about social mobility in Chile? This is the question we aim to explore in this article. We begin by reviewing the existence evidence while complementing it to explore the underlying mechanisms that drive intergenerational mobility in Chile. Our work is divided into three parts. We begin with a general presentation of existing estimates. Second, we explore the role of parental education in shaping income inequality, and how its importance varies for different groups. We finish by providing a summary measure of intergenerational persistence, which we use to explore the relationship between persistence and income inequality.

Existing estimates of intergenerational mobility show that persistence in Chile is quite high. While all available data is subpar for this type of analysis, whether it is surveys or administrative records, all estimates show a somewhat consistent picture of relatively high persistence. Interestingly, whenever studies find evidence of a higher degree of mobility, it is because of their focus on the lower parts of the distribution. Income inequality in Chile is highly concentrated at the top, which allows for higher mobility for low and middle income groups, as small differences in their income can move them considerably across the distribution. This is what Torche (2005) calls an `unequal but fluid' pattern, with relatively mobility for most of the population, and a small but highly unequal group at the top where mobility (both into this group but also within it) is strongly constrained.

The available data from household surveys shows a very clear socioeconomic gradient based on parental education. Around half of those whose parents had a tertiary degree come from the top 20% of the income distribution. On the other hand, between a third and 40% of respondents whose parents had no education come from the bottom 20%. We find that social benefits alleviate to some degree this trend, but not to a large degree. Moreover, we show that this socioeconomic gradient has held over time, at least since 2006, and that the main differences appear to be between those whose parents had a tertiary degree and the rest. Indeed, these differences has been growing over time, suggesting the presence of unequal gains from economic growth. However, since 2013 this group has seen a slowdown in their income growth – but not enough for the remaining groups to catch up. Overall, parental education is an important determinant of current income inequalities, accounting for 46% of total inequality measured through the Gini coefficient.

We also explore the relative importance of parental education across different demographic and socioeconomic groups. Doing so gives us an idea of the groups in which parental schooling plays the largest role in shaping outcomes. We find that that parental schooling is particularly relevant in the fishing and health industries, in the Metropolitan Region of Santiago, and among individuals in prime working age (35 to 44) as well as pensioners (over 75). The common thread across these groups is that there is a high degree of income dispersion within each one. Groups with a high degree of inequality also show a higher degree of heterogeneity of socioeconomic background, such that these ascriptive characteristics play a larger role.

One case is particularly helpful in explaining this relationship between inequality and persistence. If we focus solely on the group that identifies with the Mapuche ethnicity we find that parental schooling plays a limited role. This is a relatively homogeneous groups from a socioeconomic perspective and ascription does not play a considerable role. If, on the other hand, we look at the region with the highest share Mapuche population we find that parental schooling is particularly relevant. This is because the largest income differences in this region are between the indigenous and non-indigenous population. Our findings suggest that parental schooling plays a bigger role in shaping inequality on groups based on geographical location or industrial activity rather than groups based on individual characteristics such as ethnicity, age, education or gender. These are more heterogeneous in terms of individual characteristics which means that, first, there are more internally unequal groups and, second, groups where individual characteristics play a larger role. In other words, we find that more socioeconomically diverse groups are both more unequal and suffer from a higher degree of intergenerational persistence.

To further explore this association we estimate the intergenerational elasticity of income, a summary measure that represents the association between the income of the parents and that of their children. This is done through a prediction approach which we describe in the Appendix. Our estimates of the intergenerational elasticity for household income are consistent with previous studies, at 0.64. This is a strong degree of intergenerational association, higher than for Europe or even the US or China. The use of a single summary measure allow us to provide two further exercises. First, we find a positive association at the regional level between income inequality and intergenerational persistence, consistent with previous studies that have studied this association across countries. Second, we show that intergenerational persistence grows with income. Both are findings are consistent with the idea that inequality is closely associated with persistence across generations, and that groups or categories where socioeconomic dispersion is higher will tend to have both higher inequality and higher dispersion.

Overall, our findings show that Chile is a Chile where social mobility is limited, but with some degree of heterogeneity. Mobility is feasible in the lowest rungs of the income distribution as small differences in income result in considerable movement. However, this is not the case as we move further up the income distribution as moving into these groups requires a considerable increase in come. Given the nature of the income distribution we mobility at the top to be considerable limited and mostly driven by the characteristics of their parents. This to be the case whether we are focusing on high-status based on education, occupation or income. Moreover, our findings suggest a strong and positive association between inequality and intergenerational persistence, where they interact and reinforce each other.

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Tables

Table 1: Descriptive statistics across sociodemographic groups, including the between-share of per capita income inequality

	Median Income	Average Income	Mean to median ratio	Relative Income	Between share (Gini)	Population Share
Gender						
1. Hombre	$ 310,834	$ 502,882	1.62	1.1	47%	56%
2. Mujer	$ 276,167	$ 419,474	1.52	0.9	44%	44%
Age						
25-34	$ 309,167	$ 519,734	1.68	1.1	46%	15%
35-44	$ 270,000	$ 483,848	1.79	1	51%	18%
45-54	$ 276,250	$ 445,033	1.61	1	42%	22%
55-64	$ 310,208	$ 462,296	1.49	1	45%	20%
65-74	$ 310,000	$ 462,686	1.49	1	47%	15%
75+	$ 304,646	$ 415,852	1.37	0.9	50%	10%
Indigenous						
Non-indigenous	$ 301,667	$ 477,515	1.58	1	46%	92%
Mapuche	$ 229,850	$ 326,475	1.42	0.7	37%	7%
Other indigenous	$ 270,953	$ 427,557	1.58	0.9	41%	1%
Region						
1. Región de Tarapacá	$ 305,000	$ 420,892	1.38	0.9	22%	2%
2. Región de Antofagasta	$ 392,500	$ 600,163	1.53	1.3	40%	3%
3. Región de Atacama	$ 321,264	$ 439,725	1.37	0.9	33%	2%
4. Región de Coquimbo	$ 235,500	$ 319,771	1.36	0.7	39%	4%
5. Región de Valparaíso	$ 300,595	$ 439,604	1.46	0.9	32%	10%
6. Región del Libertador Gral. Bernardo O'Higgins	$ 253,014	$ 335,104	1.32	0.7	32%	5%
7. Región del Maule	$ 219,646	$ 309,815	1.41	0.7	33%	6%
8. Región del Biobío	$ 249,308	$ 363,991	1.46	0.8	42%	9%
9. Región de La Araucanía	$ 224,151	$ 335,258	1.50	0.7	45%	6%
10. Región de Los Lagos	$ 250,000	$ 369,465	1.48	0.8	46%	5%
11. Región de Aysén del Gral. Carlos Ibáñez del Campo	$ 388,137	$ 566,952	1.46	1.2	42%	1%
12. Región de Magallanes y de la Antártica Chilena	$ 433,375	$ 598,417	1.38	1.3	26%	1%
13. Región Metropolitana de Santiago	$ 360,000	$ 586,829	1.63	1.3	50%	41%

16. Región de Ñuble	$ 212,643	$ 297,582	1.40	0.6	31%	2%
Occupation						
0. Fuerzas Armada	$ 374,532	$ 484,394	1.29	0.9	45%	1%
1. Miembros del poder ejecutivo y de los cuerpos legislativo	$ 663,333	$ 1,034,153	1.56	2	43%	7%
2. Profesionales, científicos e intelectuales	$ 851,162	$ 1,141,656	1.34	2.2	28%	14%
3. Técnicos profesionales de nivel medio	$ 481,722	$ 651,566	1.35	1.2	26%	10%
4. Empleados de oficina	$ 316,667	$ 388,374	1.23	0.7	17%	6%
5. Trabajadores de los servicios y vendedores de comercio	$ 270,277	$ 335,676	1.24	0.6	23%	14%
6. Agricultores y trabajadores calificados agropecuarios y pesq	$ 231,942	$ 311,065	1.34	0.6	23%	4%
7. Oficiales, operarios y artesanos de artes mecánicas y de otr	$ 257,377	$ 327,328	1.27	0.6	19%	14%
8. Operadores de instalaciones y máquinas y montadore	$ 285,745	$ 357,239	1.25	0.7	21%	10%
9. Trabajadores no calificado	$ 229,917	$ 276,337	1.20	0.5	16%	20%
Industry						
1. Agricultura, ganadería, caza y silvicultura	$ 221,858	$ 305,116	1.38	0.6	33%	8%
2. Pesca	$ 238,739	$ 437,003	1.83	0.8	55%	1%
3. Explotación de minas y canteras	$ 420,000	$ 642,342	1.53	1.2	41%	2%
4. Industrias manufactureras	$ 292,917	$ 428,817	1.46	0.8	33%	10%
5. Suministro de electricidad, gas y agua	$ 359,805	$ 557,451	1.55	1.1	47%	1%
6. Construcción	$ 280,300	$ 439,325	1.57	0.8	41%	9%
7. Comercio al por mayor y al por menor	$ 282,500	$ 401,752	1.42	0.8	35%	18%
8. Hoteles y restaurantes	$ 310,625	$ 443,470	1.43	0.8	30%	4%
9. Transporte, almacenamiento y comunicaciones	$ 321,944	$ 469,725	1.46	0.9	37%	8%
10. Intermediación financiera	$ 666,667	$ 897,068	1.35	1.7	43%	2%
11. Actividades inmobiliarias, empresariales y de alquiler	$ 521,375	$ 859,272	1.65	1.6	44%	8%
12. Administración pública y defensa	$ 452,813	$ 693,705	1.53	1.3	44%	6%
13. Enseñanza	$ 447,222	$ 641,694	1.43	1.2	32%	7%
14. Servicios sociales y de salud	$ 498,971	$ 917,124	1.84	1.8	48%	5%
15. Otras actividades de servicios comunitarios, sociales y p	$ 351,080	$ 559,957	1.59	1.1	46%	3%
16. Hogares privados con servicio doméstico	$ 258,750	$ 298,770	1.15	0.6	16%	6%
ESEC						
1. Large employers, higher mgrs/professionals	$ 804,167	$ 1,128,746	1.40	2.2	31%	14%
2. Lower mgrs/professionals, higher supervisory/technicians	$ 585,359	$ 865,935	1.48	1.7	37%	10%
3. Intermediate occupations	$ 400,000	$ 534,818	1.34	1	24%	9%
4. Small employers and self-employed (non-agriculture)	$ 276,206	$ 416,952	1.51	0.8	31%	19%
5. Small employers and self-employed (agriculture)	$ 216,250	$ 294,539	1.36	0.6	22%	3%
7. Lower sales and service	$ 290,000	$ 354,259	1.22	0.7	22%	11%
8. Lower technical	$ 258,000	$ 325,336	1.26	0.6	19%	10%

9. Routine	$ 245,350	$ 298,628	1.22	0.6	19%	24%
Education						
0. Sin Educ. Formal	$ 209,578	$ 236,458	1.13	0.5	6%	2%
1. Básica Incom.	$ 218,888	$ 255,561	1.17	0.5	7%	14%
2. Básica Compl.	$ 233,333	$ 273,590	1.17	0.6	12%	12%
3. M. Hum. Incompleta	$ 251,667	$ 303,007	1.20	0.6	17%	11%
4. M. Téc. Prof. Incompleta	$ 300,000	$ 365,956	1.22	0.8	16%	2%
5. M. Hum. Completa	$ 262,500	$ 334,123	1.27	0.7	17%	21%
6. M. Téc Completa	$ 273,444	$ 343,059	1.25	0.7	14%	7%
7. Técnico Nivel Superior Incompleta	$ 328,958	$ 439,020	1.33	0.9	24%	2%
8. Técnico Nivel Superior Completo	$ 394,000	$ 523,861	1.33	1.1	15%	8%
9. Profesional Incompleto	$ 429,333	$ 603,003	1.40	1.3	25%	4%
10. Postgrado Incompleto	$ 1,075,000	$ 1,315,311	1.22	2.8	35%	1%
11. Profesional Completo	$ 686,506	$ 955,468	1.39	2	24%	14%
12. Postgrado Completo	$ 1,291,875	$ 1,694,302	1.31	3.6	21%	2%
Income Poverty						
1. Pobres extremos	$ 58,114	$ 53,889	0.93	0.1	26%	2%
2. Pobres no extremos	$ 93,882	$ 96,082	1.02	0.2	16%	5%
3. No pobres	$ 314,578	$ 494,882	1.57	1.1	46%	93%
Income decile						
1	$ 97,925	$ 91,440	0.93	0.2	10%	10%
2	$ 146,444	$ 145,908	1.00	0.3	4%	10%
3	$ 186,584	$ 186,587	1.00	0.4	3%	10%
4	$ 225,921	$ 226,051	1.00	0.5	4%	10%
5	$ 270,000	$ 270,988	1.00	0.6	2%	10%
6	$ 325,000	$ 325,372	1.00	0.7	2%	10%
7	$ 397,003	$ 396,776	1.00	0.9	5%	10%
8	$ 501,842	$ 506,865	1.01	1.1	6%	10%
9	$ 712,138	$ 731,800	1.03	1.6	15%	10%
10	$ 1,403,000	$ 1,783,347	1.27	3.8	19%	10%
Full sample	$ 296,667	$ 466,462	1.57	1	46%	100%

Table 2: The intergenerational elasticity of household income

	(1)	(2)	(3)
Parental income (log)	0.585***	0.605***	0.649***
	(0.015)	(0.014)	(0.022)
Age (centred at 40)		0.005**	-0.022
		(0.002)	(0.068)
Age^2		-0.000	0.012
		(0.000)	(0.010)
Age^3		0.000	-0.000
		(0.000)	(0.001)
Age^4		-0.000	-0.000
		(0.000)	(0.000)
Parental income x Age			0.002
			(0.005)
Parental income x Age^2			-0.001
			(0.001)
Parental income x Age^3			0.000
			(0.000)
Parental income x Age^4			0.000
			(0.000)
Constant	6.073***	5.830***	5.251***
	(0.192)	(0.184)	(0.282)
Observations	35,137	35,137	35,137
R-squared	0.167	0.175	0.176

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

Appendix

The estimation of an intergenerational elasticity (IGE)

Existen múltiples formas de medir movilidad intergeneracional. Tal vez la principal distinción está entre medidas absolutas y medidas relativas. Una medida absoluta compara la situación de padres e hijos independiente de su posición en la distribución de ingresos. Es decir, se concentra en si los hijos han logrado un mayor nivel de ingresos, educación, etc., que sus padres. Por otro lado, las medidas relativas de movilidad sí toman en cuentan la posición tanto de hijos como de padres, y nos informan de la asociación. Como es de esperar, un país puede tener movilidad absoluta pero no relativa, o viceversa.

Tal vez las dos medidas relativas más conocidas en el estudio de la desigualdad económica son la elasticidad intergeneracional y la correlación en ranking (Rank-rank correlation). La primera estudia la asociación entre el ingreso de padres e hijos de forma directa:

$$y_h = \alpha + \beta y_p + \varepsilon$$

Donde y_h es el ingreso del hijo y y_p el ingreso de los padres. En este caso nuestro estimador de interés es $\hat{\beta}$. Si tanto el ingreso del hijo como de los padres están en logaritmo, entonces podemos interpretar este estimador como una elasticidad. Es decir, si $\hat{\beta} = 0.2$, entonces 20% de las brechas de ingreso entre familias permanecen de una generación la siguiente.

La correlación en ranking es una medida puramente posicional. En vez de preguntar por la asociación entre el ingreso de padres e hijos, se pregunta por la asociación entre las posiciones relativas de padres e hijos. Por ejemplo, si agrupamos tanto a padres como a hijos en 100 grupos con igual número de personas (percentiles), entonces esta correlación se estima a través de:

$$rank_h = \tau + \rho\, rank_p + \mu$$

Donde el estimador relevante es $\hat{\rho}$. Un estimador de $\hat{\rho} = 0.4$ quiere decir por cada 10 percentiles de diferencia en los padres (un decil), sus hijos experimenten 4 percentiles de diferencia.

¿Cuál es la relación entre ambas variables? Múltiples artículos muestran que ambos estimadores están estrechamente relacionados. Si definimos σ_p y σ_h como la desviación estándar del ingreso para padres e hijos respectivamente, entonces:

$$\beta = \rho \frac{\sigma_h}{\sigma_h}$$

Es decir, si aumenta la desigualdad en la generación de los hijos (σ_h sube), entonces la elasticidad intergeneracional aumenta mientras que la correlación se mantiene constante. En otras palabras, la movilidad intergeneracional (β) considera también la variabilidad en la desigualdad en ambas generaciones importante medir ambos estimadores al momento de describir la movilidad relativa entre padres e hijos.

Data requirements and alternative estimation methods

El estudio de la asociación entre padres e hijos requiere información detallada de ambos. Para estimar esta asociación de forma efectiva se necesita tener en cuenta la edad en que observamos los ingresos tanto de padres como de hijos. Una edad muy temprana no refleja aún la capacidad total de generar ingresos de un adulto, de la misma forma que los ingresos durante la jubilación representan un nivel menor al recibido en el mercado laboral. En ese sentido, la literatura recomienda centrarse en individuos entorno a los 40 años de edad (Haider and Solon, 2006; Lee and Solon, 2009).

Tal vez la mejor alternativa para este tipo de análisis son los datos longitudinales de larga extensión. Estos permiten seguir a los mismos individuos a lo largo de múltiples periodos, pudiendo así promediar sus ingresos a través de varios periodos. De esta forma es posible tener una mejor idea de los ingresos 'permanentes' de estas personas, suavizando el ruido que generan periodos de cesantía o inactividad. Si los datos longitudinales son suficientemente largos, también es posible asociar padres e hijos en la misma encuesta. Estimaciones como estas son comunes en países con este tipo de datos, como es el caso de Estados Unidos (Mazumder, 2018) o Inglaterra (Blanden et al., 2007).

En el caso de no tener este tipo de datos, Björklund y Jäntti (1997) proponen una alternativa conocida como *Two-Sample Two-Stage Least Squares* (TSTSLS). Esta alternativa requiere datos de corte transversal para así buscar información de los potenciales padres de una cohorte determinada. Para esta metodología se requieren al menos dos años de datos, los datos primarios con la información de los hijos y datos secundarios con información de los padres, típicamente observados cuando los hijos tenían entre 14 a 16 años. Por ejemplo, si nos concentramos en personas con 40 años en 2017, necesitamos entonces una encuesta de principios de 1990 para buscar a los padres.

En primer lugar, se identifica que información de los padres ha sido entregada por los hijos. Esto incluye típicamente la educación de los padres y a veces otra información adicional. Usando los datos secundarios se estudia la relación entre ingreso parental y estas características para así predecir el ingreso de los padres en los datos primarios. El resultado es una base de datos con el ingreso predicho de estos padres 'sintéticos'. Si bien estudios recientes han demostrado que TSTSLS suele sobreestimar la asociación entre pares (Jerrim et al., 2016), este método nos permite una primera aproximación para estimar la asociación intergeneracional en un contexto de escasez de datos.

Our estimation of the IGE relies on a rough TSTSLS approach to estimate the intergenerational elasticity (IGE) of household income. We use both the education of both parents as well as the district (*comuna*) of residence at age 16 to predict parental income in 2017. The 'first-stage' estimation looks at heads of households with children that were 0 to 28 years of age in 1990, which we then use in our 'second stage', predicting that income for respondents age 27 to 55 in 2017. The resulting IGE estimates are reported in Table 2. As mentioned before, TSTSLS typically overestimates the IGE, so these estimates should be treated as the upper bound of the 'real' intergenerational elasticity.

Decomposition of inequality indexes

Any inequality index can be decomposed into a within and a between-group component. Intuitively, the between-group component represents the extent of inequality when all people within a group have the same income, equal to the average of their group. Within-group inequality, on the other hand, represents the extent of inequality when only focusing on a single group. Averaging inequality across these groups with weights equal to the relative size of each groups gives us a measure of overall within-group inequality. While this decomposition is straightforward, not all inequality indexes can be additively decomposed into these two parts.

In other words, the sum the within and between inequality does not necesarilly equal totally inequality. This is certainly not the case for the Gini coefficient, which can be decomposed into three terms, a within term, a between term, and a residual terms that represent the extent to which the different group distributions overlap. As shown in Mussard et al. (2003), the decomposition of the Gini coefficient be written as follows, given the overall definition of the Gini:

$$Gini = \frac{\sum_{i=2}^{n}\sum_{r=1}^{n}|y_i - y_r|}{2n^2\mu} = G_w + G_b + G_t \tag{1}$$

Where y_i represents the income of individual i, μ the average income and n the size of the population. The within-group component can be defined as:

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j \tag{2}$$

Where G_{jj} is the Gini for group j, p_j the share of individuals in group j and s_j the share of income held by group j. The between group is then defined as:

$$G_b = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh} D_{jh} (p_j s_h + p_h s_j) \tag{3}$$

Where G_{jh} is the Gini between groups j and h, and D_{jh} a measure of distance between the two groups. Finally, the third term capturing the overall between the different group distributions is given by:

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh} (1 - D_{jh})(p_j s_h + p_h s_j) \tag{4}$$

Another measure of inequality, the Theil index, also known as the Mean Logarithmic Deviation (MLD), can be decomposed additively into only two components, with no residual term. Such that the sum of the within and between-group components add up to the total index. Using the same definitions, the Theil can be defined as:

$$Theil = \frac{1}{n}\sum_{j=1}^{k}\sum_{i=1}^{n_j}\frac{y_{ji}}{\mu}log\left(\frac{y_{ji}}{\mu}\right) = T_w + T_b \tag{5}$$

Where the within-group component is defined by:

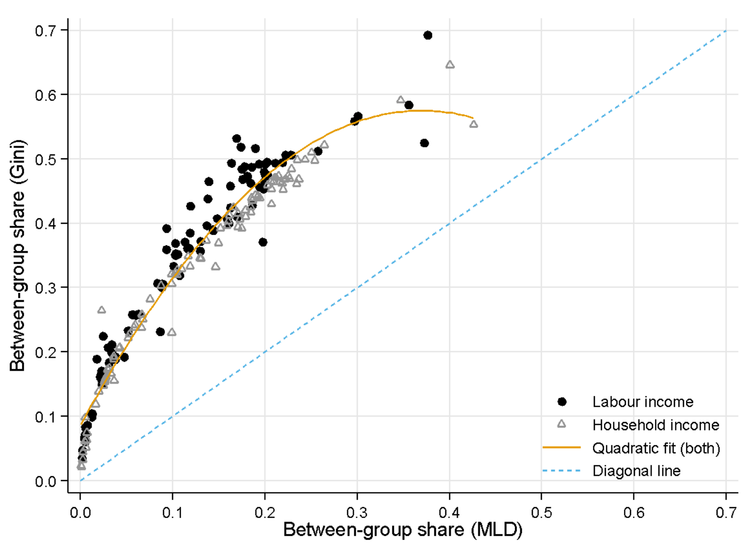
$$T_w = \sum_{j=1}^{k}\frac{n_j\mu_j}{n\mu}log\left(\frac{\mu_j}{\mu}\right) \tag{6}$$

And the between-group component equals:

$$T_b = \sum_{j=1}^{k}\frac{n_j\mu_j}{n\mu}\frac{1}{n_j}\sum_{i=1}^{n_j}\frac{y_{ji}}{\mu_j}log\left(\frac{y_{ji}}{\mu_j}\right) \tag{7}$$

While the Gini and the Theil provide different decompositions, and therefore different shares, we see that they impose the same ranking. Figure C1 shows that the two decomposition are positively but nonlinearly related. These estimates follow from the discussion in section 3.2. Due to its nature, the between-component under the Gini coefficient will always be higher than the MLD component. Indeed, this is one of the criticisms that the latter suffers – that the between-group component will be artificially too low due to having fewer groups than individuals in each group. This is now known as the ELMO critique, named after Elbers, Lanjouw, Mistiaen and Ozler (2008). In fact, we see a concave relationship between the two, with higher between-group inequality under the MLD resulting in higher between-group inequality under the Gini, but increasing at decreasing rates.

Figure C1: Between-group inequality under two different inequality indexes



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