Intergenerational Earnings Mobility in Chile: A tale of two tails

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Abstract

This paper provides the first consistent estimates of intergenerational earnings mobility in Chile, based on administrative records that link a child's and their parent's earnings from the formal private labour sector. We estimate that the intergenerational earnings elasticity is between 0.288 and 0.323, whereas the rank-rank slope is between 0.254 and 0.275. We find significant non-linearities in the intergenerational mobility measures, where intergenerational mobility is very high in the bottom 80% of the parents' distribution but with extremely high intergenerational persistence in the upper part of the earnings distribution.

1 Introduction

This paper asks whether the association between parents' and their child's earnings in Chile varies with parental earnings level and children's place of residence. Chile is an interesting

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case study not only due to having made significant progress in its economic development in the last three decades (reaching a GDP per capita of US$ 16,143 in 2018, IMF, 2018) but also because it is one of the countries with the most unequal income distribution in the world. It has a Gini index of 0.444 points (World Bank, 2020), and the fraction of the country's total income received by the richest 10% of the population is extremely high (37.1%) when compared to the OECD average of 24.8% (OECD, 2020). Moreover, conservative estimates suggest that the share of total income that the richest 1% take is 15%, while less conservative estimates establish it at 22-26% (Fairfield and Jorrat, 2016; Flores et al. 2019).

Under what conditions an unequal society can be tolerated is a subject of longstanding debate, especially in Chile. Supporters of meritocracy argue that economic inequality can be legitimated in a society if income differences stem from differences in reward for talent, hard work and skill, but not due to luck or transmission of advantages. According to this view, income inequality should not be tolerated in a society with less social mobility and greater transmission of privileges or disadvantages from parent to child, where children born in poverty (richness) remain in poverty (richness) in their adulthood, regardless of their skills or efforts. In part, the de-legitimization of income inequality is one of the main causes behind the social outbreak that occurred in Chile in October 2019, when the perception of unfairness in the distribution of income and privileges provoked lower and middle classes to take to the streets to express their indignation with the current situation. In this context, understanding social mobility in Chile is crucial to disentangle the origins of its current levels of economic inequality.

In this paper, we study intergenerational mobility in Chile by building a new and unique data set after assembling three administrative data sources. We obtain information on labour earnings of children and their parents from 2002 to 2019 from the database of the Chilean government's unemployment insurance program (UIP). We link children and their parents using administrative records provided by the Civil Registry Office. We obtain the place of residence of a child when they were between 13 and 18 years old from administrative records at the Ministry of Education. To the best of our knowledge, this is the first work that uses administrative information to estimate intergenerational mobility for a non-advanced economy.

We estimate intergenerational earnings mobility at the national level. We find that it is highly non-linear in Chile, and intergenerational mobility is very high for the bottom 80 percent of the earnings distribution, and exceed the rate of intergenerational mobility in

advanced countries such as the US and Canada. But earnings are also highly persistent for the upper decile of the earnings distribution, much more so than for any advanced economy.[1] We can summarize this finding as: intergenerational churning, and socio-economic uncertainty, for the masses contrasts with secure inherited privilege for the elite.

We also make a methodological contribution: we use for the first time tools to estimate intergenerational mobility at the top of the distribution such as RIF regressions and Kernel conditional densities.

Of course, there is a vast body of literature from economists trying to learn about social mobility from administrative records in advanced economies. For the United States, there is a series of articles that are based on a project by Raj Chetty, Nathaniel Handren and others, who use administrative tax data to estimate the intergenerational elasticity of income.[2] For example, the work of Chetty et al. (2014) studies how social mobility varies through geographic zones called community zones in the US. For Canada, the literature on intergenerational income mobility starts with the seminal work of Corak and Heisz (1999), a pioneering paper in the use of administrative data to study intergenerational mobility of income. More recently, Corak (2019) studies intergenerational mobility in Canada utilizing census data and analyzing data at various geographic levels. Europe has also produced some interesting literature in this regard. For instance, Acciari et al. (2019) use tax data to investigate how intergenerational mobility varies geographically for Italy, as do Güell et al. (2015) for social mobility at smaller geographical units in Italy, which Heidrich (2017) also does for Switzerland. Most of these works for developed countries show that disaggregated geographical measures of intergenerational mobility provide evidence of significant heterogeneities across locations that are hidden in country-level estimates.

In the case of Chile, our work does not emerge in a vacuum. Over the last two decades, some papers have made progress in understanding social mobility by using survey data. For example, Nuñez and Miranda (2010, 2011) study intergenerational income mobility by using the Two-Sample Two-Stage Least Squares (TSTSLS) methodology developed by Björklund and Jäntti (1997). Sapelli (2013) provides evidence on changes in the intergenerational mobility of education through time, using several cross-section surveys. Meanwhile, Torche

[1] This result resembles what Bratsberg et al. (2008) find when comparing the Nordic countries with the US and UK.

[2] In this paper, we make the distinction between earnings, for which the source is wages, and income, for which the sources are wages and financial asset income. Our study is developed with earnings due to the available dataset.

(2005) analyzes the intergenerational mobility of education based on survey data, and Celhay et al. (2010) focus on the study of intergenerational mobility of income and schooling for the period 1996-2006 using longitudinal surveys. The only paper that uses administrative records to capture a specific dimension of intergenerational mobility in Chile is the work of Zimmerman (2019). Based on a regression discontinuity design, this article illustrates the lack of upward mobility by showing that studying at an elite university has a positive effect on obtaining a managerial position with high income in the labour market, but only for those with a high-level socioeconomic background who had studied at an elite private school. This study, in part, quantifies the importance of contact networks in the generation of inequality in Chile.

2 Development of the income intergenerational mobility literature

Are the children of the poor doomed to stay poor? Are the children of the rich destined to stay rich? How difficult is it for someone who was born poor to belong to the middle class during her adulthood? These questions have been addressed at the international level, where there is vast literature on intergenerational income mobility. Jäntti and Jenkins (2015) and Corak (2013) summarize the historical results in this literature. Corak and Heisz (1999) were the first to use high-frequency administrative data on the income of parents and children in adulthood in their seminal study on intergenerational mobility in Canada.[3] This study was so innovative and ahead of its time that it took 15 years for literature to replicate this study for other countries. In fact, thanks to the development of computer science and generalization in the use of administrative data, the literature of intergenerational mobility has been given a new lease of life. The works of Chetty et al. (2014), Chetty et al. (2017), and Chetty et al. (2018a, 2018b) have extensively studied intergenerational mobility in the United States using the same type of data.

Undoubtedly, the novelty of these studies is in the data used, which mainly correspond to confidential high-frequency administrative data that cover a sufficiently long period and link the income of the parents with the adult income of their children. The advantage of

[3]Others important studies on intergenerational mobility for Canada are Fortin and Lefebvre (1998), and Simard-Duplain and St-Denis (2020)

administrative data is that they do not have the traditional problems present in household surveys. In fact, traditional household surveys in general are not longitudinal but cross-sectional, which makes it difficult to obtain information on the income of the parent and child in adulthood. In addition, household surveys have problems such as sampling, self-reporting and non-response, and it is known that non-response rises as the respondent's income increases (Bollinger et al., 2018).

Understanding the intergenerational mobility of income in the United States has been tremendously important in understanding the generation of inequality. There is a series of articles that are based on a project by Raj Chetty, Nathaniel Handren and others, who use administrative tax data to estimate the intergenerational elasticity of income. The work of Chetty et al. (2014) studies geographic zones called community zones. The abovementioned investigation by Chetty and others differentiate between absolute and relative intergenerational mobility, which has been of interest to both politicians and researchers. The Canadian literature on intergenerational income mobility starts with the seminal work of Corak and Heisz (1999), pioneering in the use of administrative data to study intergenerational mobility of income. More recently, Corak (2019) studied intergenerational mobility in Canada, using census data and analyzing intergenerational mobility within Canada at a geographic level. Acciari, Polo and Violante (2019) investigate intergenerational mobility for Italy by taking tax data, also analyzing what happens geographically. Finally, this literature has also progressed in Europe, mostly based in the Nordic countries. Jäntti (2006) illustrates very well the use of these data. Also, there are the studies for Switzerland by Heidrich (2017) and Güell et al. (2015) for Italy. Both studies are at the provincial and inter-country levels.

2.1 Intergenerational mobility of income, the case of developing countries

Research on intergenerational mobility of income in developing countries faces additional complications. Having longitudinal data that gather parents and children is very difficult (Daude and Robano, 2015, Neidhöfer, 2019, Neidhöfer et al., 2018) due to the limitation of household surveys and/or the difficulty of accessing administrative data.

One way to address the limitations of the data is to restrict the analysis to children and parents living in the same household or to impute an income for the parents based on multiple waves of a household survey. For example, Lambert et al. (2014) studies intergenerational

mobility in Senegal and Torche (2014) summarizes intergenerational mobility in Latin America from studies that have used surveys as a primary source of information.

Recently, progress has been made to investigate intergenerational mobility using census data from 26 African countries (Alesina et al., 2019) and for the regions of India, Asher et al. (2018). In this context, our research project will be pioneering in Latin America because it uses administrative data, which is the way in which the frontier literature is studying intergenerational mobility.

3 Data

3.1 Information on labour earnings

We obtain the information on labour earnings of children and their parents from the database of the UIP in Chile. The UIP is a benefit that covers all employees in the private sector over 18 years old and with a formal contract, whether fixed-term or permanent. Participation in the scheme is mandatory for all contracts started after September 2002 and voluntary for contracts started before that date. This means that these administrative records contain the monthly labour earnings of all employed workers over the age of 18 who initiated a work-under-contract relationship in the private sector from October 2002 to December 2019. This data set also includes the workers with labour contracts established prior to October 2002 who voluntarily joined the UIP. It is worth mentioning that this data set excludes workers with training contracts, workers under the age of 18, domestic workers, pensioners, self-employed or own-account workers, and public sector employees.

Table 1 provides information on the proportion of workers covered by the UIP over several years. As can be seen, due to the voluntary retroactive nature of the UIP policy, the coverage rate for formal contract workers was below 50% in 2003 and 2004. In the following years, this coverage rate significantly increased, attaining 65% in average in 2005-2007 and 80% in 2012. Part of the 20% of formal contract workers still not covered by the UIP in 2012 are public sector employees, who are covered under a similar but separate scheme. Table 1 also shows information on workers covered by the UIP as a proportion of the total labour force. Initially, the labour force coverage rate was 42% in average for the years 2003-2007, which

rapidly converged to 65% in 2012. The 35% not covered by the UIP in 2012 is explained by public sector employees, the unemployed, and informal workers.[4]

Table 1: Representativity of the unemployment insurance program dataset.

Year	Total UIPD	W ENE	Coverage W	LF ENE	Coverage LF
2003	1349.5	3672.7	36.7%	5119.1	26.3%
2004	1849.5	3806.3	48.6%	5286.1	34.9%
2005	2337.8	3987.4	58.6%	5438.7	43.0%
2006	2701.3	4166.4	64.8%	5442.2	49.6%
2007	3103.1	4360.3	71.1%	5555.5	55.8%
2008	3309.2	4583.5	72.2%	5762.4	57.4%
2009	3419.8	4500.1	76.0%	5839.9	58.6%
2010	3742.4	4908.1	76.2%	6210.1	60.2%
2011	4050.4	5146.7	78.7%	6448.8	62.8%
2012	4286.4	5360.2	80.0%	6520.0	65.7%

This dataset is compared with the information of the ENE (Encuesta Nacional de Empleo) questionnaire administred by the goverment statistics agency in Chile (INE-Instituto Nacional de Estadisticas). W ENE refers to the total number of formal employees recorded by ENE and LF ENE is the total labour force (formal and informal) recorded by ENE. The information regarding ENE numbers is from Sehnbruch and Carranza (2015). Units are measured on thousands

We must acknowledge that the low formal contract workers' coverage rate during the first years of the data (56% in average in 2003-2007) is a concern for our analysis because —as explained below— it impacts how we model permanent parental earnings for our baseline sample. To assess the plausibility of our findings, we perform a robustness exercise. We frame our analysis using data for years with a higher formal contract workers' coverage rate to construct the permanent parental earnings.

[4]As we can see, this dataset converges to a coverage rate of 80% of the formal workers but only to 65% for the total labour force. This is in part because this dataset has limited coverage for the (cont'd) unemployed. Sehnbruch (2006) and Ruiz-Tagle and Sehnbruch (2010) argue that this is because a large proportion of unemployed register by ENE previously worked in the informal sector.

3.2 Information on child-parent linkage

We link children and their parents using administrative records provided by the Civil Registry Office (CRO). In Chile, the CRO registers all births, deaths, and marriages. It is a legal requirement in Chile that all births must be registered in the CRO, each of which is backed by a birth certificate. This birth certificate contains the information on the child and the parents given at the time of registration. We use the information provided for all the birth certificates in Chile to build the pairs of children and parents included in the UIP database.[5] In our baseline analysis, the sample of children is composed of individuals that were 28-33 years old in 2018, while the sample of parents are individuals that were 42-87 years old in 2018.

3.3 Measurement of earnings

Our administrative records have information on labour earnings in the formal private sector, excluding any form of capital income for the workers covered by the UIP. In our baseline sample, we measure parental earnings as the 5-year average of monthly earnings for months worked in the formal private sector between 2003 and 2007. For example, if a parent records 30 months worked within a 5-year period, the measure of earnings used is the total income in those 5 years divided by 30. In our baseline sample, we only consider parents that worked at least 6 months in the formal private sector during 2003-2007. If both parents worked more than 6 months in the period, we consider the average parental earnings as the sum of parental earnings divided by two, in line with Chetty et al. (2014) and Corak (2019).

Our measure of parental earnings excludes the zeros because a zero in our data set does not mean that the individual has no earnings, since he/she could be earning as a public employee, in the informal sector, or in the formal private sector but not covered by the UIP, especially in its earlier years.

As with the parents, we measure child earnings in our baseline sample as the five-year average of monthly earnings for worked months in the formal private sector between 2014 and 2018. In our baseline analysis, we consider children that worked at least six months in the formal private sector in 2014-2018. This measure of child earnings not only excludes the zeros for the same reasons as for their parental earnings, but also because children may start

[5]Families are ever changing, so the parenting person or persons at any point in time may not be the birth parents.

participating in the private formal labour market in their late 20s, giving a series of months with earnings preceded by a series of zeros corresponding to not being in the labour market.

To minimize the noise provoked by low earners due to the uncertainty surrounding the low earnings registered with the UIP, we only consider children and parents who on average earn more than half the minimum wage.[6] In our baseline sample, we have 505,524 parent-child links.

3.4 Comparison between unemployment insurance program dataset and ENE survey

In Chile, 29.6 percent of the population works the informal sector. One potential issue for our dataset is that only contains information on private formal earnings. To see how different are the percentiles including all workers, we compare the earnings percentiles generated by our dataset and the Encuesta Nacional de Empleo (ENE).

[6]Half the minimum wage for children is $133,000 in 2019 Chilean pesos (measured from 2014 to 2018) and $103,000 in 2019 Chilean pesos for parents (from 2003 to 2007). Using CASEN 2017 information, 14.1 percent of the population were under the minimum wage.

Table 2: Comparison of earnings between our dataset and ENE for individuals between 28-33 years old.

Percentile	UIP	ENE
1%	152,889	170,613.6
5%	218,433	231,840
10%	263,508	250,902
25%	343,076	330,000
50%	490,707	451,624
75%	767,851	700,000
90%	1,173,052	1,003,609
95%	1,544,161	1,304,692
99%	2,371,979	2,500,000

This dataset is compared with the information of the ENE (Encuesta Nacional de Empleo) questionnaire administred by the goverment statistics agency in Chile (INE-Instituto Nacional de Estadisticas). W ENE refers to the earnings percentiles for all workers – formal, informal and self employed. Units are in 2018 Chilean pesos.

Table 2 compares our dataset earnings percentiles with ENE dataset percentiles for 2018. We can see that percentiles similar using the whole population and types of sector and the formal private sector.

4 Intergenerational mobility for Chile

We begin our empirical analysis by characterizing the relationship between parental and child earnings at the national level. We present a set of baseline estimates of relative intergenerational mobility and then evaluate the robustness of our estimates to alternative samples.

4.1 Traditional indicators of intergenerational mobility

4.1.1 Intergenerational earnings mobility

One of the most commonly used measures of intergenerational mobility is the intergenerational earnings elasticity, i.e., the effect that a 1 percent increase in the parental earnings has over their child's earnings. In our work, we estimate the intergenerational elasticity of earnings rather than of income because our dataset only contains information on wages and not on financial asset income. We measure this elasticity by estimating the following equation:

$$y_i^c = \alpha + \beta y_i^p + \epsilon_i, \tag{1}$$

where y_i^c is the earnings of child i in logarithms, y_i^p is the earnings of that child's parents in logarithms, and β is the intergenerational earnings elasticity. This parameter is equal to

$$\beta = \frac{cov(y_i^p, y_i^c)}{var(y_i^p)} = \rho \cdot \frac{sd(y_i^c)}{sd(y_i^p)}, \tag{2}$$

where ρ is the intergenerational earnings correlation, and $sd(y_i^c)$ and $sd(y_i^p)$ are the standard deviation of child and parental log earnings, respectively. To prevent any attenuation bias, we measure child and parental earnings as the 5-year average of earnings.

Table 3: OLS estimates of the intergenerational earnings elasticity for our baseline linkage

	(1)	(2)	(3)	(4)
y_p	0.288***	0.297***	0.311***	0.323***
	(0.001)	(0.001)	(0.002)	(0.002)
Constant	9.506***	9.426***	9.298***	9.193***
	(0.016)	(0.018)	(0.021)	(0.027)
Observations	505,524	416,818	282,979	173,683
R-squared	0.091	0.098	0.108	0.117

Standard errors in parentheses

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

Earnings are measured as average earnings over the months where a children-parents pair report positive earnings over the studied 5-year period. We keep individuals that appear at least 6 times with positive earnings in the dataset with average earnings greater than half of the corresponding minimum wage. Columns (1) to (4) report results for male and female children. (1) considers individuals with at least 6 months of positive earnings, (2) considers individuals with at least 12 months of positive earnings, (3) considers individuals with at least 24 months of positive earnings and (4) considers individuals with at least 36 months of positive earnings.

Table 3 summarizes our estimates for intergenerational earnings elasticity (IGE), i.e., the OLS estimates of the regression slope of the log child earnings on log parental earnings. Columns (1) to (4) report results for male and female children: (1) considers individuals with at least 6 months of positive earnings (our baseline sample); (2) considers individuals with at least 12 months of positive earnings; (3) considers individuals with at least 24 months of positive earnings; and, (4) considers individuals with at least 36 months of positive earnings.

Our baseline estimation for IGE equals 0.288. With our most restrictive sample — individuals with at least 36 months of positive earnings—, this estimate equals 0.323. This means that an increase of 10 percent in parental earnings implies, on average, an increase of between 2.88 and 3.23 percent in their child's earnings.[7]

[7]This estimate is lower compared with previous estimates in the Chilean literature. Nunez and Miranda (2010,2011), and Celhay et al. (2010) estimate an elasticity between 0.5 and 0.6. Our differences can be

Table 4: OLS estimates of the intergenerational earnings elasticity for female children

	(1)	(2)	(3)	(4)
y_p	0.300***	0.307***	0.315***	0.326***
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	9.253***	9.209***	9.169***	9.086***
	(0.024)	(0.026)	(0.032)	(0.042)
Observations	222,397	178,916	116,182	68,644
R-squared	0.103	0.111	0.119	0.128

Standard errors in parentheses

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

Earnings are measured as average earnings over the months where a children-parents pair report positive earnings over the studied 5-year period. We keep individuals that appear at least 6 times with positive earnings in the dataset with average earnings greater than half of the corresponding minimum wage. Columns (1) to (4) report results for male and female children. (1) considers individuals with at least 6 months of positive earnings, (2) considers individuals with at least 12 months of positive earnings, (3) considers individuals with at least 24 months of positive earnings and (4) considers individuals with at least 36 months of positive earnings.

explained by the kind of data used and the method implemented to estimate IGE. Appendix C discusses this point in detail.

Table 5: OLS estimates of the intergenerational earnings elasticity for male children

	(1)	(2)	(3)	(4)
y_p	0.282***	0.294***	0.314***	0.329***
	(0.002)	(0.002)	(0.002)	(0.003)
Constant	9.655***	9.529***	9.313***	9.175***
	(0.022)	(0.024)	(0.028)	(0.036)
Observations	283,127	237,902	166,797	105,039
R-squared	0.087	0.094	0.107	0.117

Standard errors in parentheses

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

Earnings are measured as average earnings over the months where a children-parents pair report positive earnings over the studied 5-year period. We keep individuals that appear at least 6 times with positive earnings in the dataset with average earnings greater than half of the corresponding minimum wage. Columns (1) to (4) report results for male and female children. (1) considers individuals with at least 6 months of positive earnings, (2) considers individuals with at least 12 months of positive earnings, (3) considers individuals with at least 24 months of positive earnings and (4) considers individuals with at least 36 months of positive earnings.

Tables 4 and 5 estimate the IGE for female and male children respectively. Our results suggest that female children are slightly less intergenerationally mobile than male children.

4.1.2 Rank-rank correlation

Another measure of intergenerational mobility that has become extremely popular is rank-rank correlation. This correlation measures the effect that an increase of a percentile in the parental earnings distribution has over the child earnings distribution. One of the arguments to use rank-rank correlation is that the rankings on the earnings distribution are determined at earlier ages and are difficult to change throughout the age distribution. We measure this correlation by estimating the following equation by OLS:

$$r_i^c = \alpha^r + \beta^r r_i^p + \epsilon_i, \tag{3}$$

where r_i^c is the ranking of i-th child in the national distribution of child earnings by cohorts, r_i^p is the ranking of i-th child's parent on the national distribution of parental earnings, and β^r is the rank-rank correlation.[8] This correlation is an indicator of relative mobility that compares the maximum influence of parental ranking on expected child ranking. In addition, α^r is a measure of absolute mobility because it states the expected ranking that a child would have if her parents belong to the bottom of the parental earnings distribution.

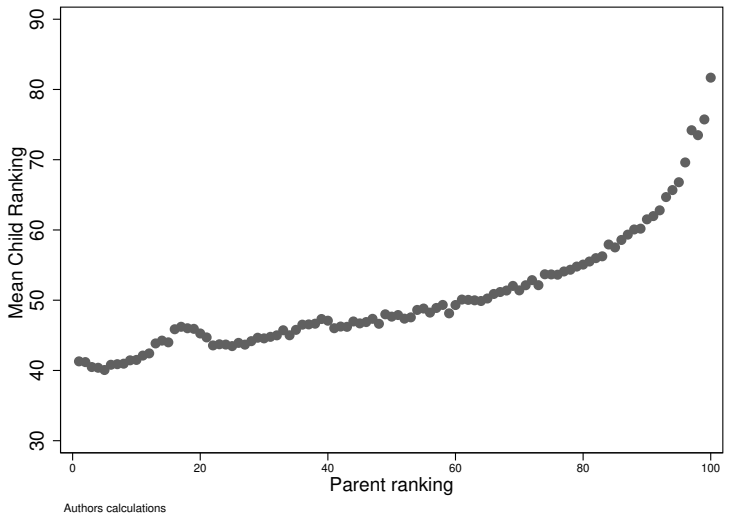

Figure 1: Expected child ranking conditional on parental ranking

We estimate the expected child ranking non parametrically using a simple average. Rankings were computed over the national distribution. For children we compute the cohort ranking, and for parents we compute the ranking of people 42-87 years old (in 2018).

Figure 1 presents a binned scatter plot of the mean percentile rank of children versus their parents' percentile rank. This graph illustrates a nonparametric estimation of the conditional expectation of a child's rank given her parents' rank ($E[r_i^c|r_i^p = p]$). As we can see, the relationship between parental ranking and child ranking is close to a linear function until the 80th parental percentile, while for parental percentiles higher than 80 it is highly non-linear with an increasing gradient as the parental ranking increases.

[8]Note that we compute the ranking of the whole cohort of children and parents, regardless of whether they are linked.

Table 6: OLS estimates of the rank-rank correlation for our baseline linkage

	(1)	(2)	(3)	(4)
r^p	0.254***	0.261***	0.270***	0.275***
	(0.001)	(0.001)	(0.002)	(0.002)
Constant	37.397***	38.668***	40.859***	43.368***
	(0.080)	(0.089)	(0.110)	(0.141)
Observations	505,524	416,818	282,979	173,683
R-squared	0.064	0.068	0.073	0.078

Standard errors in parentheses

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

Earnings are measured as the average earnings over the months in which an individual reports positive earnings over 5 years. We keep children-parents linkages that appear at least 6 times with positive earnings in the dataset with average earnings greater than half of the corresponding minimum wage. Columns (1) to (4) report results for male and female children. (1) considers individuals with at least 6 months of positive earnings, (2) considers individuals with at least 12 months of positive earnings, (3) considers individuals with at least 24 months of positive earnings and (4) considers individuals with at least 36 months of positive earnings.

Table 6 presents our estimates for the rank-rank slope. To measure the percentile rank of the children, we consider their rankings in the distribution of child earnings within their birth cohorts. In the same way, we compute the percentile rank of the parents from their positions in the distribution of parental earnings in the baseline sample. Based on the child and parental percentile ranks, the rank-rank slope estimate is the OLS estimate of the regression slope of the percentile rank of a child on the percentile rank of her parents. As before, columns (1)-(4) in Table 6 present the results for 6 (baseline sample), 12, 24, and 36 months of positive earnings. The rank-rank correlation is between 0.254 and 0.275, that is, the maximum expected difference in child earnings rankings that depends on parental ranking is between the 25th and 28th child earnings percentiles.

Table 7: OLS estimates of the rank-rank correlation for our female children

	(1)	(2)	(3)	(4)
r^p	0.278***	0.285***	0.293***	0.300***
	(0.002)	(0.002)	(0.003)	(0.004)
Constant	31.669***	33.234***	35.762***	38.362***
	(0.121)	(0.138)	(0.176)	(0.233)
Observations	222,397	178,916	116,182	68,644
R-squared	0.075	0.079	0.083	0.088

Standard errors in parentheses

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

Earnings are measured as the average earnings over the months in which an individual reports positive earnings over 5 years.We keep children-parents linkages that appear at least 6 times with positive earnings in the dataset with average earnings greater than half of the corresponding minimum wage. Columns (1) to (4) report results for male and female children. (1) considers individuals with at least 6 months of positive earnings, (2) considers individuals with at least 12 months of positive earnings, (3) considers individuals with at least 24 months of positive earnings and (4) considers individuals with at least 36 months of positive earnings.

Table 8: OLS estimates of the rank-rank correlation for our female children

	(1)	(2)	(3)	(4)
r^p	0.239***	0.247***	0.258***	0.264***
	(0.002)	(0.002)	(0.002)	(0.003)
Constant	41.682***	42.504***	44.118***	46.312***
	(0.103)	(0.114)	(0.139)	(0.175)
Observations	283,127	237,902	166,797	105,039
R-squared	0.060	0.064	0.070	0.076

Standard errors in parentheses

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

Earnings are measured as the average earnings over the months in which an individual reports positive earnings over 5 years. We keep children-parents linkages that appear at least 6 times with positive earnings in the dataset with average earnings greater than half of the corresponding minimum wage. Columns (1) to (4) report results for male and female children. (1) considers individuals with at least 6 months of positive earnings, (2) considers individuals with at least 12 months of positive earnings, (3) considers individuals with at least 24 months of positive earnings and (4) considers individuals with at least 36 months of positive earnings.

Table 7 show the rank-rank correlation estimates only for female children, and Table 8 show rank-rank correlation estimates for male children. Comparing female and male, results show that the rank-rank correlation is higher for female children. This indicates that for females, parental ranking is more persistent than for males. In addition, absolute mobility, measured as the constant of each regression, is higher for males than for females, which means that male children of poor parents are expected to locate in a higher ranking than female children of poor parents.

4.1.3 Quintiles transition matrices

These child and parental earnings rankings also allow us to estimate the quintile transition probabilities. These probabilities are defined by the conditional probability that a child is in quintile m (with $m = 1, 2, 3, 4, 5$) of the child earnings distribution given that her parent is in quintile n (with $n = 1, 2, 3, 4, 5$) of the parental earnings distribution.

In the intergenerational mobility literature, there are three probabilities that are broadly studied: i) the circle of poverty, defined by the probability that, given parents who belong to the bottom quintile, the child will also belong to the bottom quintile. We denote this probability as p_{11}; ii) the circle of privilege, defined by the probability that, given parents who belong to the top quintile, the child will belong to the top quintile. We denote this probability as p_{55}; and, iii) the rags to riches, defined by the probability that, given parents who belong to bottom quintile, the child will belong to the top quintile. We call this probability p_{15}. Notice that p_{11} and p_{55} are measures of intergenerational persistence that provide evidence on transmission of disadvantages and advantages, respectively; while p_{15} is a measure of upward intergenerational mobility.

Table 9: Transition matrix of parental earnings quintiles to child earnings quintiles

		Child quintile				
		1	2	3	4	5
Parental quintile	1	0.271	0.235	0.204	0.170	0.120
	2	0.236	0.235	0.213	0.186	0.130
	3	0.206	0.223	0.220	0.200	0.150
	4	0.171	0.193	0.215	0.223	0.198
	5	0.112	0.125	0.161	0.226	0.376

Quintiles are measured using earnings and the baseline dataset. Rows refer to parental quintile and columns to child quintiles.

Table 9 shows the matrix of quintile transition probabilities using our baseline sample. As can be seen in Table 9, p_{11} is equal to 0.271 meaning that a child whose parents belong to the bottom quintile has an observed probability of 27.1 percent of remaining in the bottom quintile; p_{55} is equal to 0.376, which means that a child whose parents belong to the top quintile has a probability equal to 37.6 percent of remaining in the top earnings quintile; and p_{15} is equal to 0.120 which means that the probability that a child whose parents belong to the bottom quintile will herself belong to the top quintile is 12 percent.

Our results suggest that there is some persistence of parental earnings because p_{55} and p_{11} are higher than 0.2, which is the value of a transition probability, assuming that parental-child transitions are random. We also find that $p_{55} > p_{11}$ meaning that persistence is higher at the top of the distribution than at the bottom. Notice that the transition probabilities of the first 4 quintiles are relatively similar and close to random transitions; however, our results reveal that the main departure from randomness occurs at the top quintile where there is a notorious intergenerational earnings persistence.

4.1.4 International comparison with the US and Canada

To put our analysis in perspective, we can compare Figure 1 with findings for the US and Canada. As reference, we use the results in Chetty et al. (2014) for the US, and the findings

in Corak (2019) for Canada. Notice that, whereas for Chile we use earnings information, the works of Corak (2019) and Chetty et al. (2014) use income information.[9]

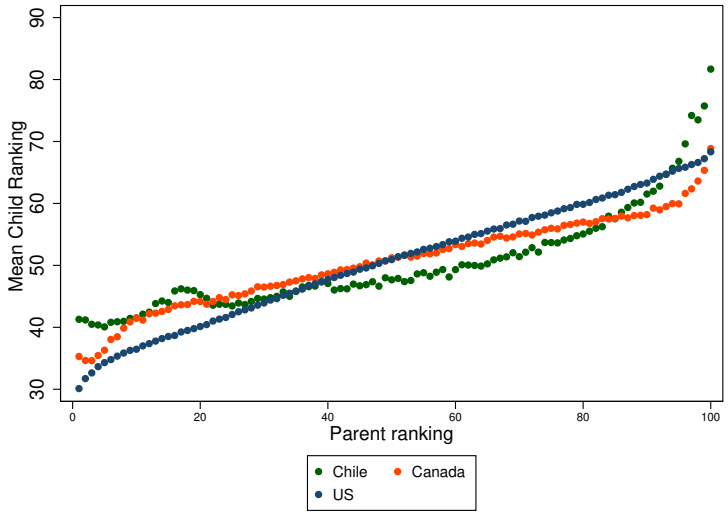

Figure 2: International comparison of expected child earnings ranking conditional to the parental earnings ranking

We estimate the expected child ranking non parametrically using a simple average. Rankings were computed over the national distribution. We compute the cohort ranking for children and for parents we compute the ranking of people between 42 and 87 years old (in 2018). Information for Canada is from Corak (2019) and for the US is from Chetty et al. (2014).

Figure 2 shows that Chile has a flatter gradient until the 80 percent in parental income/earnings. This evidence suggests that Chile is more mobile than Canada and the US in parental income/earnings until the 80th percentile. Remarkably, after the 80th parental percentile, Figure 2 also shows that the relationship between parental and child earnings in Chile becomes much steeper than those in the US and Canada. This graphical analysis suggests that intergenerational earnings mobility for Chile is much more non linear than the results found by the US and Canada.

[9]Studies show that income is more persistent than earnings, especially at the bottom of the distribution. Thus, our results for Chile can be interpreted as a lower bound for persistence.

4.2 More on non-linearities

The previous graphical analysis suggests that the relationship between parental and child earnings in Chile is highly non-linear, even more so than in the US and Canada, with the particularity of displaying significant intergenerational mobility until the 80th parental earnings quintile but a notorious degree of persistence of privileges (transmission of advantages from parent to child) at the top of the earnings distribution.

To better understand this finding, we perform three empirical exercises. First, we show the estimates of the transition probabilities for the top decile and percentiles. Second, we estimate the conditional distribution of child earnings given a parental decile (percentile), for different parental deciles (percentiles). Finally, we again estimate the IGE equation but, instead of using OLS, we use conditional and unconditional quantile regressions.

4.2.1 Decile and percentile intergenerational transition matrices

We now present decile transition probabilities. These estimates allow us to gain deeper understanding on how the child earnings distribution behaves within quintiles —especially for children with parents in the top quintile. Table 10 shows the matrix of decile transition probabilities.

As can be seen in Table 10, the transition matrix —excluding the row with the 10% richest parents— shows a somewhat intergenerationally-mobile context, with all the transition probabilities roughly close to 10%, as we would expect under random transition from parent to child. However, given the parental earnings top decile, we notice that the dynamic of the transition probabilities is significantly different. For instance, the probability of persistence in privilege p_{1010} is equal to 0.3. In contrast, the probability of persistence in poverty p_{11} is close to a half of p_{1010}, suggesting that the transmission of advantages (circle of privilege) is twice as persistant as the transmission of disadvantages (circle of poverty).

We now study p_{1010} in depth by showing the probabilities associated with transitions from parental percentiles to child percentiles, for percentiles from 91 to 100. Table 11 summarizes this information.

As can be seen in Table 11, the transition probabilities for children whose parents belong to the 91st to 95th percentiles of the parental earnings distribution are relatively similar, while the probability of persistence at the top percentile, $p_{100,100}$, is significantly higher compared to

Table 10: Decile Transition Matrix

		Child deciles									
		1	2	3	4	5	6	7	8	9	10
Parental deciles	1	0.158	0.136	0.125	0.114	0.104	0.098	0.086	0.073	0.065	0.042
	2	0.125	0.123	0.118	0.114	0.107	0.099	0.094	0.085	0.075	0.059
	3	0.122	0.126	0.124	0.114	0.111	0.102	0.095	0.085	0.072	0.050
	4	0.109	0.115	0.118	0.114	0.110	0.104	0.101	0.091	0.079	0.060
	5	0.106	0.107	0.112	0.117	0.112	0.108	0.102	0.093	0.083	0.061
	6	0.096	0.104	0.108	0.109	0.110	0.111	0.106	0.099	0.091	0.066
	7	0.086	0.093	0.100	0.104	0.109	0.112	0.110	0.107	0.100	0.080
	8	0.078	0.084	0.087	0.095	0.102	0.108	0.114	0.115	0.117	0.100
	9	0.067	0.069	0.073	0.080	0.091	0.099	0.110	0.127	0.140	0.143
	10	0.044	0.042	0.044	0.051	0.059	0.071	0.092	0.122	0.173	0.301

Table 11: 91st to 100th parental percentile to 91st to 100th child percentile transition matrix

		Child percentiles									
		91	92	93	94	95	96	97	98	99	100
Parental percentile	91	0.019	0.018	0.017	0.019	0.020	0.019	0.017	0.019	0.019	0.023
	92	0.020	0.017	0.019	0.020	0.019	0.020	0.018	0.018	0.022	0.021
	93	0.019	0.021	0.020	0.019	0.024	0.019	0.025	0.023	0.021	0.023
	94	0.021	0.022	0.021	0.022	0.028	0.025	0.022	0.021	0.024	0.025
	95	0.024	0.022	0.018	0.027	0.025	0.026	0.029	0.031	0.028	0.027
	96	0.026	0.025	0.026	0.026	0.028	0.026	0.032	0.034	0.033	0.039
	97	0.024	0.025	0.032	0.033	0.035	0.038	0.042	0.043	0.050	0.056
	98	0.024	0.023	0.026	0.029	0.035	0.038	0.042	0.042	0.045	0.057
	99	0.026	0.029	0.030	0.029	0.032	0.043	0.039	0.047	0.055	0.066
	100	0.027	0.035	0.035	0.029	0.045	0.051	0.056	0.060	0.068	0.105

the rest of transition probabilities presented in Table 11. This means that the top percentile is even more persistent than the rest of the 10th decile. In sum, this analysis provides evidence supporting a high persistence at the top, which increases as long as parental earnings increase.

4.2.2 Conditional distribution of child earnings, given parental deciles

Another way to understand the association between child and parental earnings is by estimating the conditional distribution of child earnings, given parental earnings $f(y^c|y^p)$. Thus, instead of just observing a change in the mean, we can study variations in the entire distribution. To do this, we perform kernel estimations of the conditional distribution of child earnings, given parental deciles.

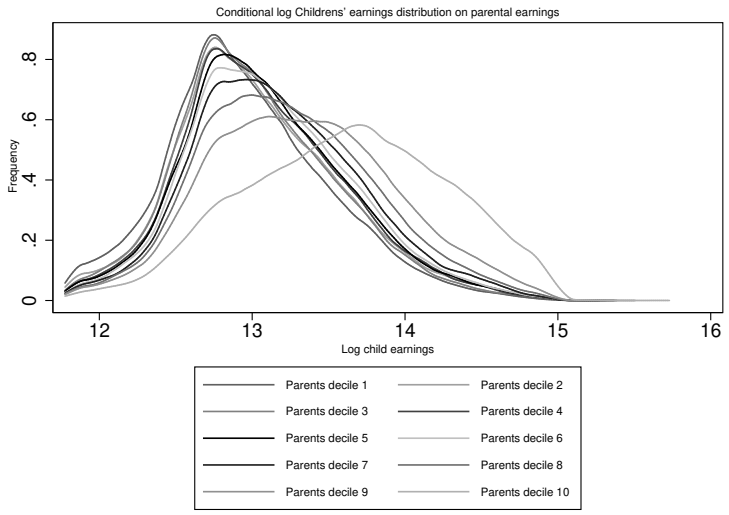

Figure 3: conditional (on parental deciles) child earnings distribution

This figure estimates conditional (on parental deciles) child earnings distribution, using kernel to estimate child earnings distribution. We use the Epanechnikov method to estimate optimal bandwith.

Figure 3 shows the conditional distribution of the logarithm of child earnings given that parents belong to a particular earnings decile, for earnings deciles from 1 to 10. As can be seen in Figure 3, roughly speaking, the conditional distributions of child earnings are unchanged between parental decile 1 and 7. After decile 8, it tends to move. Indeed, conditional on parents belonging to the top decile, the conditional distribution of log child earnings is significantly shifted to the right. This evidence is consistent with our previous findings of

transmission of privileges, since it suggests that it is more likely for children whose parents belong to the top earnings decile to obtain higher earnings. As can be also seen in Figure 3, the conditional distribution of log child earnings for top parental earnings has a higher variance than conditional on lower parental earnings. In sum, this analysis supports the idea that for children in the bottom and middle part of the earnings distribution, parental earnings do not affect their own distribution of earnings; however, child earnings located at the top of their distribution are dramatically affected by parental earnings.

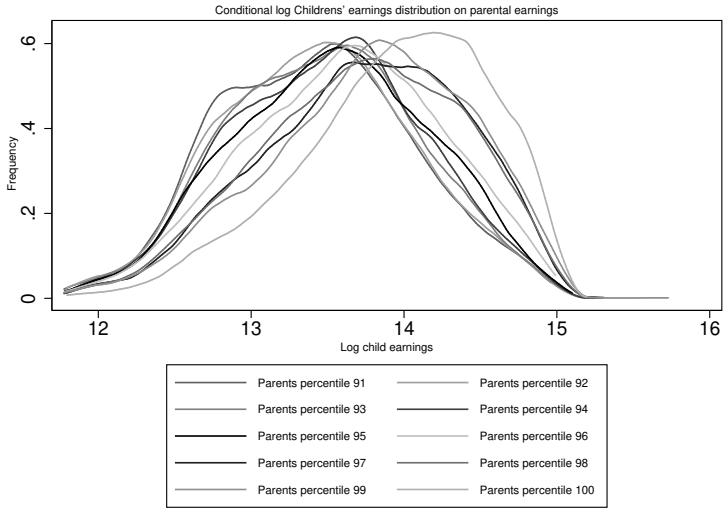

Figure 4: onditional (on parental percentiles in the top decile) child earnings distribution

This figure estimates conditional (on parental percentiles in the top decile) child earnings distribution, using kernel to estimate child earnings distribution. We use the Epanechnikov method to estimate optimal bandwith.

Figure 4 presents the estimation of the conditional distribution of log child earnings, given parents that belong to a specific percentile, for percentiles from 91 to 100. As can be seen in Figure 4, while the conditional distribution of child earnings is quite similar for those with parents in percentiles 91 to 99, it is starkly different when we condition by parents belonging to the top 1 percent. This evidence supports our finding that the relationship between parental and child earnings is highly non-linear, even at the top parental distribution where this relationship becomes significantly more positive.[10]

[10]This result is in line with Zimmerman's (2019) findings. Zimmerman (2019) shows that studying in an elite college only increases the probability of belonging to the top managerial positions (obtaining higher

4.2.3 Unconditional and conditional quantile regressions

The two previous empirical analyses provide evidence on non-linearities in the relationship between parental and child earnings when conditional on parental earnings. In other words, as long as parental earnings increase, there is a higher persistence of child earnings, especially at the top of the parental earnings distribution. However, we can also study the non-linearities in this relationship, conditional on child earnings. Specifically, given a child earnings percentile, is the effect of an increase in parental earnings stronger? We answer this question by using quantile regressions.

The IGE is estimated using OLS as the expected percent change in average child earnings, given an increase of 1 percent on the average parental earnings. Additional information regarding the relationship between parental and child earnings can be obtained by estimating the effect of a change in parental earnings on any other distributional moments of child earnings other than the mean.

We can estimate, for instance, the effect of an increase in parental earnings on the median, the 75th percentile, or the bottom 5 percentiles of the child earnings distribution. The magnitude of those effects would allow us to understand more in depth where in the child earnings distribution an increment of the parental earnings can improve their outcome. We obtain these effects by fitting quantile regressions. Following the works of Firpo, Fortin and Lemieux (2009) and Baltagi and Ghosh (2017), there are two effects of an increase in parental earnings over the quantile distribution of child earnings: a "between effect" and a "within effect". The between effect is defined by the increase in expected child earnings due to an increase in parental earnings, while the within effect is given by the change in child earnings variance associated with a change in parental earnings. Relying on these works, a conditional quantile regression allows us to estimate the between effect, and an unconditional quantile regression is useful to estimate both effects. Thus, the analysis of both methodological instruments would allow us to understand more about the observed non-linearities in the association between parental and child earnings estimated so far.[11] Figure

earnings) if the student attends a top private high school, and he also shows that it is more likely that parents that belong to the top 1 percent can afford the tuition costs of private schools. Thus, Zimmerman's findings are one component of this persistence at the top where the transmission of privileges from parent to child would be through paying the tuition costs for attending a top private high school.

[11] Appendix B explains with more detail the relationship between conditional and unconditional quantile regressions.

5 presents the estimates of the unconditional quantile and conditional quantile regressions in our applications.

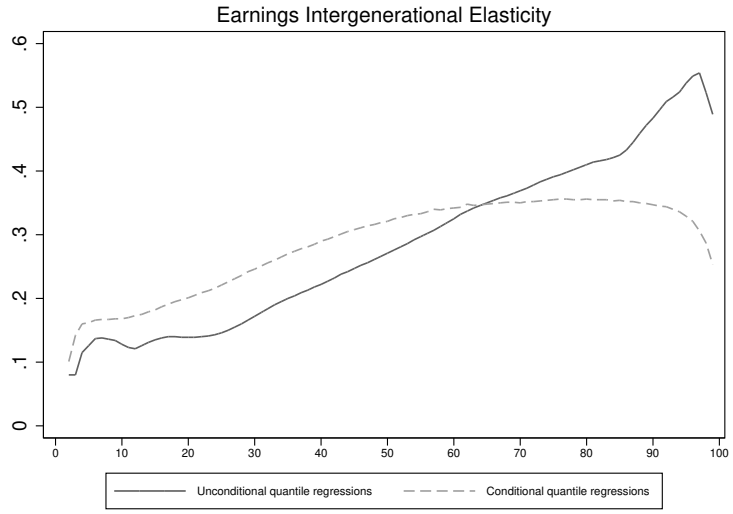

Figure 5: Unconditional quantile and conditional quantile estimates of the regression slope of log child earnings vs log parental earnings

Unconditional quantile and conditional quantile estimates of the regression slope of log child earnings vs log parental earnings for the 1st to the 99th child earnings percentiles. Unconditional quantile regressions are estimated using the RIF methodology developed by Firpo, Fortin and Lemieux (2009).

As can be seen in Figure 5, the unconditional quantile effect is lower than the conditional quantile effect until the 65th child percentile. This suggests that for the first 65 percentiles, the between effect is mitigated by the effect that an increase in parental earnings has over the child earnings variance. Meanwhile, for higher percentiles, the between effect is reinforced by the within effect, since an increment of parental earnings increases the variance of child earnings. These findings can be interpreted as that, at some point of the child earnings distribution, there are some higher-reward job opportunities that may be available that increase expected child earnings and the child earnings variance for those who can access these work positions.[12] To sum up, this analysis reveals that intergenerational earnings mobility in Chile is high and stable for the bottom 65% of the children earnings distribution; however, for the rest of the population economic status is highly persistent.

[12]This interpretation can be related with the results found by Zimmerman (2019) because the children who can access these higher-reward jobs are those with parents at the top of the earnings distribution.

4.3 Robustness checks

We now evaluate the robustness of our estimates of intergenerational mobility to alternative subsamples and specifications. We begin by evaluating three potential sources of bias: coverage of the dataset in initial years of the UIP, lifecycle bias, and attenuation bias.

4.3.1 Dataset coverage

As can be seen in Table 1, coverage of the unemployment insurance dataset in its first two years is less than 50% of total formal workers. To see whether this low coverage rate affects our baseline mobility estimates, we perform new estimates by considering different windows of years to measure permanent parental earnings.

Table 12: Estimations of IGE and rank-rank slope for different years where parental earnings were measured.

Parental year used	IGE	Rank-rank slope	N
2003-2007	0.288	0.254	504,990
2004-2008	0.288	0.256	550,668
2005-2009	0.287	0.260	584,770
2006-2010	0.284	0.263	607,545
2007-2011	0.283	0.268	622,339
2008-2012	0.281	0.270	632,820
2009-2013	0.280	0.272	636,640
2010-2014	0.278	0.272	638,481
2011-2015	0.280	0.275	637,808

Table 12 presents IGE and rank-rank slope estimates for different windows of years to build our measure of permanent parental earnings. We can see that IGE and rank-rank slope estimates do not depend on the choice of the window of years. Specifically, IGE estimates ranges between 0.278 and 0.288, whereas the rank-rank slope is between 0.254 and 0.275.

4.3.2 Lifecycle bias

Prior research has shown that measuring children's income at early ages can understate intergenerational persistence in lifetime income because children with high lifetime incomes have steeper earnings profiles when they are young (Haider and Solon, 2006, Grawe, 2006, Solon 1999). To evaluate whether our baseline estimates suffer from such lifecycle bias, we can estimate the intergenerational earnings elasticity by single child cohorts. To do this, we study the effects of parental earnings on child earnings when children are 23 to 33 years old. To be consistent with the literature (Chetty et al., 2014; Corak, 2019), we measure the effect of parental earnings when their children were teenagers.

Table 13: Estimates of IGE and rank-rank slope for different child ages.

Child age	IGE	Rank-rank	N
23	0.042	0.053	72,863
24	0.095	0.102	81,765
25	0.151	0.153	86,767
26	0.193	0.185	90,241
27	0.220	0.215	93,866
28	0.245	0.230	96,693
29	0.259	0.241	94,492
30	0.285	0.256	89,286
31	0.305	0.269	81,261
32	0.321	0.275	75,010
33	0.333	0.276	68,231

Table 13 shows the estimates of IGE and rank-rank slope by single child cohorts. We can see that intergenerational persistence rises as child age increases. This is consistent with Chetty et al. (2014). In particular, IGE is more affected by child cohorts than the rank-rank correlation, a fact that has been discussed previously in the intergenerational mobility literature.[13]

[13]Indeed, Becker and Mincer noted that if individuals can freely choose among occupations with differing age/earnings profiles, an equilibrium with equality across occupations in the net present value of lifetime earnings is consistent with (indeed predicts) inequality in annual earnings (or 5 year averages of monthly earnings), both within age cohorts and overall. In this human capital equilibrium of equality in net present

4.3.3 Attenuation bias

Earnings in a single year is a noisy measure of lifetime earnings, which attenuates estimates of intergenerational persistence (Solon, 1992). To evaluate whether our baseline estimates suffer from such attenuation bias, we provide the estimates of the rank-rank slope, varying the number of years used to build our measure of permanent parental earnings.

Table 14: Estimates of IGE and rank-rank slope using different years to average parental earnings.

Parental years used	IGE	Rank-rank slope	N
1	0.258	0.220	156,760
2	0.272	0.235	273,673
3	0.277	0.241	363,805
4	0.284	0.248	438,302
5	0.288	0.254	505,524
6	0.291	0.258	559,666
7	0.293	0.263	603,481
8	0.293	0.267	642,176
9	0.294	0.272	676,494
10	0.294	0.275	708,541

Table 14 presents the estimates of the IGE and rank-rank correlations by using different numbers of years to create the permanent parental earnings. As can be seen in Table 14, IGE remains somewhat stable after averaging 4 years, whereas the rank-rank slope varies slightly between 0.254 and 0.275 over 4 years.

5 Conclusion

This is the first paper that studies intergenerational mobility in Chile using administrative records. We build a data set that links parental and child earnings using information from

value, age/earnings profiles cross in the early thirties. Hence, annual incomes (or 5 year averages thereof) are plausible indicators of inequality of lifetime income for the 30-35 age cohort, but are heavily influenced by the fanning out of age/earnings profiles at later ages.

the formal labour sector and the place of residence of children during their adolescence. Our analysis reveals that intergenerational mobility at the national level is significantly lower than what was estimated in previous research. However, intergenerational mobility is extremely non-linear. We found that mobility is very high for the bottom 80 percent of the earnings distribution but is very persistent at the upper tail of the parental and child distributions.

Moreover, we make a some methodological contributions. We use RIF regressions and Kernel conditional densities to study intergenerational mobility at the top. Those tools help usus to show that intergenerational mobility is very persistent at the top in Chile.

This work builds on previous national literature and brings the state of research up to the robustness of analysis seen among works in developed economies. As such, not only does it provide more useful information for academics; it also provides an important counterpoint to similar works from developed economies by analyzing intergenerational earnings mobility in a non-developed [o developing] economy in a way that can be contrasted with the results of that literature. We believe that, by providing a clearer picture of how intergenerational earnings mobility occurs in Chile this work can both inspire further research on the matter both in Chile and other developing economies. These results can also help Chilean authorities better understand how and where to apply certain related social/economic programs in order to improve their impact, as well as provide input for drawing up and discussing proposed bills affected by this study's results.

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