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INEQUALITY OF OPPORTUNITIES AND LONG TERM EARNINGS MEASURES: EVIDENCE FOR CHILE

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Inequality of Opportunities and Long Term Earnings Measures: Evidence for Chile

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Abstract

In this paper we assess the sensitivity of measures of inequality of opportunity to long-term earnings data. We compare indicators using four and seven year earnings with indicators that use the most commonly available yearly and monthly earnings. We argue that four and seven year earnings are preferable since they are a more precise measure of permanent income and are less affected by short-term variability. We use data available for Chile and found that the use of seven and four year earnings produces a 25% higher share of inequality of opportunity compared to yearly and monthly earnings measures. We find that parental education contributes most to income inequality in Chile. Finally, we perform Monte Carlo simulations, finding that our results are robust to several income processes.

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1. Introduction

The ideal of equality of opportunity appeals to many. A society that achieves equality of opportunity is seen as one that has successfully combined fairness and economic efficiency. Despite the above, monitoring and evaluating the distribution of opportunity has been hindered in the past by lack of suitable indicators. However, this situation has started to change. Following Roemer's approach that classifies how socioeconomic outcomes are related to exogenous circumstances and choices, a variety of methodologies have been developed to measure the distribution of opportunity. See for example, Bourguignon, Ferreira and Menéndez (2007), Ferreira and Gignoux (2011), and Checchi and Peragine (2005). Essentially, they estimate the impact of family background and other circumstance variables on outcome or advantage variables.

A recent study by the World Bank uses these methodologies with a sample of seven Latin American countries, deriving a set of estimates that allows the ranking of these countries according to how opportunity is distributed equally or unequally (Paes de Barro et al. 2009).[1] This can be done by means of a so-called top-down approach, which relates current socioeconomic outcomes to past circumstances or by means of a so-called bottom-up approach that assesses how opportunity is distributed among children and young people.

In this paper we investigate the sensitivity of inequality of opportunity measures to long-term earnings data and its relationship with income inequality. We estimate the share of inequality of opportunity on income inequality in the Chilean economy using a top-down approach focused on the distribution of individual labor earnings. A companion paper addresses the bottom-up approach (Contreras, Larrañaga, Puentes and Rau, 2012).

Recent evidence for Latin America has shown that inequality of opportunity explains a

[1] The seven countries analyzed are Brazil, Colombia, Ecuador, Guatemala, Mexico, Panama, and Peru.

significant fraction of total income inequality and its reduction would be a significant factor to improving welfare. However, previous research has been implemented using monthly measures of earnings that are subject to measurement error and seasonality. This is particularly problematic given the high percentage of the population working in the informal labor market, subject to significant fluctuation in income and employment opportunities, segregation in the labor market, and other issues (Perry et al. 2007). At the same time, yearly income reduces seasonality, but is still affected by measurement error and the persistence of income shocks. We consider that welfare indicators should be computed using more precise estimates of permanent income. In a country like Chile with high levels of income inequality, it is particularly important to properly measure the level of opportunity inequality, especially when considering how to improve living conditions for the majority of the population.

This paper contributes to the previous literature by examining several income measures for the Chilean economy. We take advantage of a longitudinal survey available for Chile and construct four-year and seven-year earnings averages, which are a more precise estimate of permanent income than traditional monthly income and yearly data.[2] Additionally, given the low level of female labor force participation, we focus our analysis only on men.[3] We find that income inequality decreases when using longer-term measures. At the same time, the level of inequality of opportunities increases slightly, which implies that the share of inequality of opportunities increases as well, going from 16% when we use monthly and yearly data to 20% when using seven-year data. These differences show that short-term income measures can underestimate by 25% the level of inequality of opportunities. This is the first estimation in the literature that proves the importance of having longer-term measures to accurately assess the relationship between income inequality and inequality of

[2] Ferreira and Gignoux (2011) mostly use monthly data to measure wage earnings, except for self-employment in Ecuador and Guatemala, where income is measured yearly, and they use yearly data when analyzing consumption. Despite that consumption is a better measure of welfare than income, there is not any data on consumption for Chile.

[3] We observe wages only for women who work and potential earnings are therefore unobserved for many women that do not have earnings. Additionally, female labor force participation has been around 42% between 2003 and 2009 (Mideplan, 2009). Selection into the labor market could substantially affect the results for women. For that reason we constraint our analysis to men.

opportunities.

The data available for Chile consists of a longitudinal study with three waves, which collects information about labor histories. For each labor history, individuals report the length of the labor trajectory and an average wage, which allows us to construct proper measures of yearly, four-year and seven-year income measures. Also, monthly wages can be imputed form labor histories, however, by construction, monthly income is less noisy in our data than in traditional survey data. In order to analyze the potential biases that data collection could have in our calculations, we proceed to estimate Monte Carlo simulations to compare our results to different earning generation processes. We find that our results are consistent with the Monte Carlo simulations.

The results presented in this paper provide important inputs for public policy perspective and the relative effort to compensate inequality, which should be increased at least in two dimensions. First, public policy should be targeted more intensively using more innovative actions and instruments. Second, a greater funding is needed to correctly compensate for the influence of household background on health, schooling, training, and other variables that affect income and welfare. For instance, Ferreira and Gignoux (2011) show that there is a negative relationship of inequality of opportunities in educational outcomes for 15-year-old students and the share of public spending on primary education. Even though the relationship is not causal, it suggests the importance of public policy and inequality of opportunities. Additionally, these results provide ground for a conceptual discussion on compensation. Indeed, providing a foundation for redistributing current income is one way to address unfortunate childhood experiences. Given that an important fraction of income inequality can be traced back to the distribution of circumstances in early life, it can be argued that justice requires compensating for negative childhood circumstances. This argument is, of course, at the conceptual level. Its implementation in the public policy arena would require taking into account other consideration, such as the roles of information, incentives, and targeting.

The paper is organized into six sections. In section two, we present the methodology for estimating the impact of opportunity inequality in socioeconomic outcomes; section three presents the data used in this paper; section four presents and discusses the results of the inequality of opportunity measures; section five presents the Monte Carlo simulations; and in section six we present the final remarks.

2. Methodology

In this section we briefly explain the methodology implemented to measure inequality of opportunity. We closely follow Bourguignon, Ferreira and Menéndez (2007) and Ferreira and Gignoux (2011).

Roemer (1998) gives the foundation for understanding the role of inequality of opportunity in overall inequality. He postulates that advantage variables, e.g. labor earnings, are the result of two types of variables: circumstances and effort. Circumstances are variables that the individual does not have any control over, for instance the educational level of her parents. On the other hand, effort is solely based on the individual. Implicitly or explicitly, these approaches are based on model of advantage such as:

$$w = g\left(C, E, u\right)$$

where *w* denotes the outcome of interest or advantage; C denotes a vector of circumstance variables that are assumed exogenous; E denotes a vector of effort variables; and u denotes pure luck or random factors.

Following Bourguigon et al. (2007), we can approximate an advantage model by following a linear system:

$$\ln w = C\alpha + E\beta + u$$
$$E = C\lambda + v$$

where the structural equation relates income with circumstance and effort variables in log-linear way. There is also a linear equation for the effort variables that response to circumstances and an unobservable term.

The reduced form of this linear system is:

$$\ln w = C\left(\alpha + \beta\lambda\right) + v\beta + u$$

which can be estimated by OLS given the exogeneity of circumstances:

$$\ln w = C\theta + \varepsilon$$

Under these functional form assumptions, a parametrically standardized distribution $\left\{\overline{y}_i\right\}$ is estimated by:

$$\overline{y}_i = \exp\left(\overline{C}\theta_{ols} + \varepsilon_{i,ols}\right)$$

Where $\overline{C}$ corresponds to the population average of circumstances, θ_{ols} are the parameters obtained by OLS and $\varepsilon_{i,ols}$ is the individual residual.

This parametrically standardized distribution is a counterfactual distribution of income, where all differences in circumstances are eliminated and only luck and effort remain. A measure of inequality of opportunity follows naturally from these estimates:

$$S = 1 - \left[D\left(\overline{y}_i\right) / D\left(y_i\right)\right]$$

where $D(\ )$ is any inequality index calculated over the income distribution. S measures the share of inequality of opportunities in total inequality. As mentioned in Ferreira and Gignoux (2011), S is a lower bound measure of inequality of opportunities, because the part of the total distribution of income explained by all circumstances does not decrease when adding more circumstances. Then, if there are omitted circumstances, the result is a lower S.

We will also focus on the level of inequality of opportunity, which will be measured as $D\left(\overline{y_i}\right)-D\left(y_i\right)$.

Ferreira and Gignoux (2011) discuss the use of non-parametric methods to measure inequality of opportunities; these methods do not rely on functional form assumptions. We prefer a parametric method because as the vector of observed circumstances becomes larger and/or the number of categories within each variable increases, sampling variances become very large, making non-parametric estimates of inequality of opportunity too imprecise. This places an upper bound in the number of circumstances that can be included and in the number of categories within each circumstance that we can define. On the other hand, a multivariate regression framework would use data more efficiently, allowing a more detailed specification of circumstances and categories, but at the expense of imposing a given functional form to the relation between variables.[4]

Ferreira and Gignoux (2011) show how the parametric approach permits the estimation of the partial effect of one (or a subset) of the circumstance variables while controlling for others by constructing alternative counterfactual distributions, such as:

$$\overline{y}_i^K = \exp\left(\overline{C}_i^K \theta_{ols}^K + C_i^{k\neq K}\theta_{ols}^{k\neq K} + \varepsilon_{i,ols}\right)$$

[4] For a further discussion see Ferreira and Gignoux (2011).

This allows one to compute circumstance J-specific inequality shares:

$$S^K = 1 - \left[D\left(\overline{y}_i^{K}\right) / D\left(y_i\right) \right]$$

As mentioned in Ferreira and Gignoux, (2011), the calculation of partial shares assumes that the parameters are unbiased, which will not hold if the omitted opportunities in the main equation are correlated with the observed circumstances. Thus the interpretation of the shares must be done with care.

Turning to the choice of inequality indicators, the literature on inequality measurement shows that only some of the usual inequality indexes can decompose additively between-group inequality and within-group inequality (defined as the level of inequality of outcome measured within a given sub-group distribution). The best-known family of additively decomposable measures is the generalized entropy measures, among which the mean log deviation (GE(0)) and the Theil entropy (GE(1)) indexes are used in this paper.[5]

3. Data

The data used in this paper is from Encuesta de Protección Social (EPS, Social Protection Survey) from the 2004, 2006 and 2009 waves. The EPS is a longitudinal survey and follows approximately 20,000 individuals. It contains information about household composition, including individual information such as age, gender, education, and a wide range of labor market variables. Additionally, it incorporates parental data of the given individual, such as education, labor participation and characteristics of childhood household, which are key to

[5] GE(1) results are presented in the paper, and GE(0) results are presented in the appendix.

estimate the level of inequality of opportunity.[6]

One of the main advantages of using the EPS instead of other data is that we can construct four-year and seven-year labor incomes, which are more precise estimates of permanent income than monthly and yearly income, the usual variables in the literature.

In order to study how measures of inequality of opportunities change with short term or long term income, we use the same sample of individuals to eliminate composition effects from our calculations. This restriction implies that we consider only individuals with positive earnings for the whole period. Certainly this will bias the sample to the most skilled workers. Since the sample is more homogeneous in background characteristics, this could diminish the variance of the circumstances, but at the same time, income variance could also decrease. The final effect on inequality of opportunities is unclear. However, if the probability of having always-positive earnings is positively related to circumstances, then we are calculating a lower bound in the calculation of inequality of opportunities. Nevertheless, our purpose is not to derive a comparable measure of inequality of opportunity for different samples, but to examine the effects of short term vs. long term income on a given inequality measure. [7] Additionally, it is expected that skilled workers have less income variation on time, which makes it more difficult to find income inequality differences using different length of income measures.

The issue of controlling for composition effects has been considered in several methodologies that look to decompose changes of inequality in several components, such as in Juhn, Murphy and Pierce (1993), di Nardo, Fortin and Lemiux (1996), and Gosling, Machin and Meghir (2000) among others. We approach the composition issue by considering the same sample for all calculations. Additionally, it is not possible to include individuals with zero earnings at

[6] For a detailed description see Bravo et al. (2008).

[7] The percentage of men between 30 and 49 years old that have always-positive earnings over the number of men between 30 and 49 years old that have at least one monthly earning greater than zero is 61%.

any point time, since it would not be possible to calculate inequality measures considering those earnings.[8]

An important point to consider is the nature of the EPS, which does not allow us to utilize a pure monthly income measure. Individuals are asked about periods of labor activities and not for a strict monthly labor status. For instance in the 2004 EPS, participants were asked about their employment status since January 2002. Thus if one person had the same job from January 2002 until the time of the interview, he reports only one wage for the entire period. Individuals report a change in wages only when they change jobs. Using occupational information we compute a monthly wage by using the wage reported for each labor history, then if an individual had the same job from January 2002 to December 2003, the monthly wage will be the same for those 24 months. In the case that an individual changes jobs, a different wage will be reported and a new monthly wage will be imputed. In each new wave individuals are asked again about their labor histories. [9]

Then, using the 2004, 2006 and 2009 waves of the EPS, we are able to build labor histories for the period January 2002 – December 2008 and then compute monthly wages from the same period. Then, we calculate yearly, four-yearly, and seven-year measures of earnings. The monthly wage used in our calculations corresponds to June 2008, the yearly wage corresponds to wages in 2008, the four-year wage covers from January 2005 to December 2008, and the seven-year wage covers from January 2002 to December 2008.[10] The characteristic of the survey tends to decrease the variance of wages per individual over time,

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[8] In the case of the Theil index, it requires the evaluation of the logarithm of earnings, which is not possible when earnings are equal to zero. Similar calculations are made by Ferreira and Gignoux (2011).

[9] For instance, in the 2006 EPS round, individuals are asked about their labor status from January 2004 until the time of the interview, this implies a most likely change in the reported of the wage, even if individuals have the same job, which creates variance in wages per individual.

[10] Yearly, four-year and seven-year income corresponds to income averages in nominal terms. A correction to real terms is not straightforward since individuals report income for time periods and not month-by-month, Additionally when an individual reports more that one labor history, the wage reported is updated to real terms. All of these imply that the average of nominal earnings is close to the average of real earnings.

making more difficult to find differences in measures of inequality when using long-term income measures. Thus our findings can be consider as a lower bound, since more differences should be expected when using traditional measures of monthly income.

To better understand the potential biases of our estimates, we proceed to simulate the wages using Monte Carlo simulations of monthly income for a period of seven years and then calculate the indicators for monthly, yearly, four-year and seven-year income measures. The results are presented in section 5 and show that our results with the EPS are consistent with the main trends of the Monte Carlo simulations.

Considering the nature of the data, our measures of monthly and yearly income are very similar by construction, and so the more relevant comparisons in the paper are between yearly and four-year and seven-year income measures.

One issue that is often raised when measuring income inequality is that it is difficult to measure high-income groups, which is a potential problem not only for the EPS, but also for other Chilean surveys, such as the Socio-Economic Characterization Survey or Encuesta de Caracterización Socio-Económica (CASEN).[11] However, Feres (1998) and Bravo and Valderrama (2011) show that the main concern for CASEN is not labor earnings, but for capital earnings, and at the same time, the report of labor earnings tends to be consistent with National Accounts. Then, we expect this not to be a major problem for our estimates.

Table 1 shows how different income inequality measures change when we move from monthly income to yearly, four-year, and then seven-year income data.[12] It is observed that the index change is very small when comparing monthly and yearly income, due to the data characteristics described above. However, the indexes calculated using the four-year and seven-year earnings are lower than the indexes calculated using yearly and monthly measures,

[11] The CASEN is the official survey to measure poverty in Chile.
[12] We present the result for the Gini coefficient and Generalized Entropy measures because allow us to compare with relevant literature.

which supports the view that long-term measurements of income are less affected by transitory components, even in a very homogenous sample such as the one we are considering.

The level of the inequality measures shown in Table 1 are low compared to Latin American standards, Paes de Barro et al. (2007) reports that the lowest Theil index is for Panama (0.485), the differences are related to different data collection methods, in Panama the earnings data is for the previous month, in our case, the EPS data is labor histories.

Table 1: Inequality for different income measures, Men between 30 and 49 years old.

	Monthly Income	Yearly Income	Four-Year Income	Seven-Year Income
Gini coefficient	0,397	0,396	0,380	0,366
Mean log deviation	0,265	0,264	0,239	0,220
Theil index	0,301	0,301	0,275	0,253
Coefficient of variation	0,970	0,970	0,921	0,872

Notes: Seven-year income measure is the average wage from 2002 to 2008. Four-year income is the average wage from 2005 to 2008. Yearly income measured is the wage average for 2008, and monthly wage is the wage during June 2008. Number of observations is 1,611. Own elaboration.

As circumstances, we include the following variables: mother's and father's education, father's occupation, region where the individual attended primary school, and number of siblings raised in the household. Father's occupation is a dummy variable equal to one if the father was a white-collar worker, zero otherwise. The region of the primary school serves as a proxy for location of birth. Region is south if it is to the south of Santiago and north if it is north of Santiago. We do not have access to ethnicity or income data for the household were the individual was born, this implies that the level and share of inequality of opportunities includes the information of all the variables used in the estimation, plus the potential correlation with the variables not included, such as ethnicity or parent's income when the individual was a child.

Table 2 shows the main descriptive statistics of the variables used in the decomposition. As usual we observe that mean income is higher than median income, fathers and mothers have similar schooling levels, and mean number of siblings is higher than the median, implying that household size is log normally distributed.

Table 2: Descriptive Statistics, Men between 30 and 49 years old

Variable	Mean	Median	Standard Deviation
Monthly Income	357,351	250,000	351,615
Yearly Income	357,063	250,000	350,988
Four-year Income	340,943	247,500	317,712
Seven-year Income	311,968	235,714	274,883
Father was white collar	0.11	0.00	0.31
Fathers' years of schooling	5.31	5.00	4.66
Mother`s years of schooling	5.19	5.00	4.35
Lived in the South	0.22	0.00	0.42
Lived in the North	0.47	0.00	0.50
Number of Siblings	3.97	3.00	2.77

Notes: Seven-year income measure is the average wage from 2002 to 2008. Four-year income is the average wage from 2005 to 2008. Yearly income measured is the wage average for 2008, and monthly wage is the wage during June 2008. Income measures are in Chilean Pesos, in June 2008 the average exchange rate was 493 Chilean Pesos for 1 US dollar. Number of observations is 1,611. Own elaboration.

4. Results

In this section we present the results for men between 30 and 49 years old, in the appendix we show results for men between 25 and 54 years old. The age restriction allow us to partially control for the life cycle profile of wages.[13]

Table 3 shows the main results, including estimates of overall labor income inequality and inequality of opportunity levels for GE(1) measure, i.e. Theil index; and for four different income measures: seven-year average earnings, four-year average earnings, yearly average earnings and monthly earnings.[14]

[13] We use bootstrap to construct standard errors, using 200 repetitions. All calculations consider the weighting factor of the 2009 survey.
[14] In the appendix we report results for GE(0) as well.

From Table 3 we can observe that income inequality is marginally lower (but not significantly so) when using yearly income instead of monthly income. The differences in income inequality are statistically significant for longer term incomes. The level of inequality of opportunity marginally increases with long-term income measures, but the differences are not statistically significant. Finally, the share of income inequality is statistically the same for the monthly and yearly measures, but the differences are statistically different from zero for the rest of the comparisons. The fact that indexes using monthly and yearly income do not have significant differences is related to the data collection process, which makes it difficult to separate monthly and yearly income. Since the available data better permits measures of four-year and seven-year income measures, we observe statistically significant differences with the expected sign, decreasing overall inequality and increasing share of inequality of opportunities.

The fact that income inequality decreases with long-term income measures can be explained by the fact that income measured in a broader period of time contains less transitory components.

The marginal increment of inequality of opportunity suggests that circumstances are correlated to measurement error in wages and to transitory shocks, and that when those factors are taken into account, the level of inequality of opportunities increases. However, since the differences are not significant, so further evidence is needed to support that hypothesis.

Table 3: Inequality and inequality of opportunities for different income measures, men 30-49

Income Measure	Wage Inequality: Theil Index	Inequality of opportunity	Share
Seven-year	0,252	0,052	0,206
	(0,014)	(0,011)	(0,041)
Four-year	0,274	0,050	0,184
	(0,016)	(0,011)	(0,041)
Yearly	0,300	0,050	0,166
	(0,017)	(0,012)	(0,042)
Monthly	0,301	0,049	0,164
	(0,017)	(0,012)	(0,041)

Notes: Seven-year income measure is the average wage from 2002 to 2008. Four-year income is the average wage from 2005 to 2008. Yearly income measured is the wage average for 2008, and monthly wage is the wage during June 2008. Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration.

The share of inequality of opportunities increases about four percentage points or 25%, when considering long-term income measures. This result shows the importance of using long-term income measures to study inequality of opportunities, since the changes in the indicators can be of relatively large importance. This is a significant underestimation, which may affect policy recommendations in countries with high levels of inequality. Additionally, the increment in the share of inequality of opportunities indicates that measures of permanent income tend to be more correlated with circumstances of the individuals. A higher correlation with permanent income is consistent with theories of human capital formation as mentioned in Cunha and Heckman (2007) where early investment is shown to have cumulative effects on ability.

The result that inequality of opportunity increases with longer-term incomes is novel in the recently developed literature of measuring opportunities in terms of early circumstances. However, it relates to a similar result found in the literature of estimating intergenerational income elasticity. The first computations for the US economy were based on short-term income data for parents and sons, rendering estimates of the elasticity of about 0.20, which depicted an optimistic picture of social mobility in that country (Behrman and Taubman, 1985). Later, the availability of longitudinal data allowed the computation of intergenerational elasticity based on long term or permanent income of parents and sons. Now the estimates were close to 0.50, sobering the views about mobility in the US (Solon, 1989).

In a Latin American context, the share of inequality of opportunities in Chile for the monthly and yearly data (16%) is higher than for Peru (10%) and Panama (14.8%), but lower than for Colombia (19.7%), Guatemala (22.7%), Ecuador (23.7%) and Brazil (29.5%).[15]

In Table 4 we present the contribution of each circumstance variable to the inequality of opportunity. Corresponding OLS estimates are shown in the appendix.

Table 4: Decomposition by circumstance Theil Index

Income Measure	Father's Occupation	Mother's Education	Father's Education	Region	Siblings
Seven-year	0,036	0,101	0,101	0,030	0,037
	(0,010)	(0,018)	(0,020)	(0,014)	(0,005)
Four-year	0,029	0,089	0,098	0,025	0,028
	(0,008)	(0,018)	(0,021)	(0,013)	(0,005)
Yearly	0,025	0,085	0,089	0,022	0,024
	(0,007)	(0,018)	(0,021)	(0,013)	(0,005)
Monthly	0,024	0,085	0,088	0,021	0,024
	(0,007)	(0,018)	(0,021)	(0,013)	(0,005)

Notes: Seven-year income measure is the average wage from 2002 to 2008. Four-year income is the average wage from 2005 to 2008. Yearly income measured is the wage average for 2008, and monthly wage is the wage during June 2008. Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration.

The two most important circumstances contributing to inequality of opportunity are paternal

[15] Ferreira and Gignoux (2011). However, since the income measures are not directly comparable, the differences in the figures include measurement and actual opportunities differentials.

and maternal education levels. Both variables increase their importance when using long-term income measures. Interestingly we find that mother's education is not the key variable as is shown in the literature (Paes de Barros et. al (2009)). Parent's education is likely to be highly correlated with parental household income, which is a key determinant in the formation of early human capital through its impact on nutrition, health and education.[16]

Another important feature of Table 4 is the fact that the share of each circumstance individually increases when using four- and seven-year income showing that all these factors are correlated with permanent income.

Finally, from the results reported in Tables 3 and 4, it can be argued that circumstances affect inequality of opportunity in a significant manner and inequality of opportunity translates into income inequality. We can note that circumstances such as father's and mother's education account for more than 10% of inequality of opportunity and that the share related to income inequality is about 20%.

The results in this paper identify that calculation bases in short-term income measures can be misleading about the level of inequality of opportunities, however a more thorough empirical work must be done. Due to data limitations we cannot include ethnicity, which has been indicated also as an important circumstance in the Latin American context (Paes de Barros et al. (2009)). At the same time, we must resolve to obtain credible results for women, which might involve another important circumstance related to earnings and schooling.

In the next section, we present a Monte Carlo simulation that shows that we are able to capture the main trends in the calculation of inequality and inequality of opportunities.

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[16] Nuñez and Tartakowsky (2009) use the CASEN and follow the Bourguignon *et al*. They calculate that 15% of total inequality is due to inequality of circumstances. They use monthly income, a different age range, and a set of different circumstance variables, but also find that parent's education is the largest contributor to inequality of opportunity.

5. Monte Carlo simulations

In this section we present the results of Monte Carlo simulations to assess the robustness of our results to different data generating processes and the relationship of longer-term income measures and inequality of opportunity. We find that our results are consistent with several income processes, and that the data limitations of the EPS are only a factor in obtaining monthly measures. However, we are able to capture the dynamics of yearly, four-year, and seven-year earnings and inequality of opportunities measures.

To developed the Monte Carlo simulations, we use the equations developed in section two , and assume different data generation processes for the error term, which for convenience is separated into two components:

$$\varepsilon = f + n$$

where f is a permanent component, an unobserved individual fixed effect, and n is a transitory, monthly shock.

The simulation uses three circumstance variables, which are constructed from a trivariate normal distribution, with covariance matrix similar to the calculated for *father's occupation, father's education, and mother's education* for the EPS. The coefficients of the log-wage equation correspond to the ones obtain also from the actual EPS data.

We have four data generation processes, first we assume two scenarios for the correlation between f and the circumstances: zero correlation and different than zero.[17] Second, we assume that η could be *iid* or AR(1). These assumptions give four different scenarios. Monthly wages for 7-year periods are generated for a sample of 2,000 individuals, and then inequality and inequality of opportunities indexes are calculated. We replicate the results 200

[17] We assume that f has correlation 0.1 with the one of the circumstances and close to zero with the other two. The correlation between number of siblings and father's occupation is 0.1.

times for each data generation process.

Table 6 shows the results of the Monte Carlo experiment when correlation is allowed between the error term and the circumstances and η follows and AR(1) process.

Table 6: Monte Carlo simulation with AR(1) error term with no correlation between *f* and circumstances.

Income Measure	Wage Inequality Theil Index	Inequality of Opportunity	Share
Seven-year	0,221	0,028	0,125
	(0,009)	(0,004)	(0,018)
Four-year	0,223	0,027	0,121
	(0,009)	(0,004)	(0,017)
Yearly	0,232	0,027	0,118
	(0,010)	(0,004)	(0,017)
Monthly	0,244	0,026	0,108
	(0,009)	(0,004)	(0,017)

Note: Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration.

Table 6 shows that inequality decreases when long term income measures are used, also the level of inequality of opportunities decreases and the share of inequality of opportunities increases, which is consistent with our findings. We observe that inequality decreases when we move from monthly to yearly income data, which, as expected, is not observed in our results. Inequality continues to decrease when we use four-year and seven-year income measures, which is consistent with our data. Similar results are found for the rest of the scenarios (see appendix).

6. Final Remarks

This paper contributes to the existing literature by examining the sensitivity of inequality of opportunity measures to long-term earnings and its relationship with income inequality. We use four alternative measures of income for the analysis. The first two are monthly and yearly income, which are the usual measure of labor income used in the literature and are heavily exposed to transitory shocks and measurement error. The third measure is four-year income and the fourth is seven-year income, both of which are more precise estimates of permanent income, attenuating measurement error. Hence, the last two measures will allow us to more accurately understand the relationship between an individual's early life circumstances and his economic outcomes. In a country like Chile with high levels of income inequality, it is of particular interest to properly measure the level of inequality of opportunities, especially when considering how to improve living conditions of most of the population.

Our results show that using monthly or yearly measures of income can produce an underestimation of 25% in indexes of inequality of opportunities, indicating that measures of permanent income are particularly important when measuring distribution of opportunity. This is the first estimation in the literature of the importance of having longer-term measures to assess accurately the relationship of income inequality and inequality of opportunities.

In addition to measurement issues, our results show that circumstances in individuals' early lives have an impact on their adult socioeconomic outcomes. Our results find that at least 20% of labor income is correlated to circumstances in the parental household and that paternal education is the most highly correlated circumstance.

What about policy implications? Can we draw policy recommendations from an issue that has been determined in the past, as has the case of the effects of early life circumstances of the current adult population? Most policy implications about opportunity policies are related to current and future children, an issue that is addressed in a companion paper (Contreras, Larrañaga, Puentes and Rau, 2012). Our results show that current measures of inequality of opportunities could be underestimated, indicating that the efforts made to reduce inequality of opportunities have to scale-up. This should be done with innovative policies targeted to children with poor family backgrounds, especially in health and schooling. However, the budget dedicated to it must increase considerably. For example, developing countries could increase the length and scope of Conditional Cash Transfers, especially to the conditions on children's health and education, but the provision of those services has to improve to effectively decrease the levels of inequality of opportunities for future generations. Ferreira and Gignoux (2011) show negative relationships between pubic expenditure in education and inequality of opportunities of educational outcomes, suggesting that inequality indexes can be useful to measure the impact of public policy. However in order to do so, a correct measure of inequality of opportunities is needed.

For adults, a public policy focusing on a late compensation for some previous injustice could be posed. This is mainly the "redressing principle" discussed by Rawls (1971) in his famous *Theory of Justice*. In this work, the author claims that a just society is one where institutions maximize the life prospects of the most disadvantaged. To do so, society has to level the socioeconomic playing field to ensure that individuals can develop fully their talents. In addition, individuals who were not favored with talents by nature should be allocated income from redistribution financed out of taxation. On the other hand, Nozick (1974) in his response to Rawls explicitly advocates a redressing of past injustices with the main exception in his postulates that the state should confine itself to the protection of individual rights and not intervene in the allocation of income by market forces

Note that not every low-income individual qualifies for redressing, only those who experienced unfavorable early circumstances in life. According to our results, individuals whose parents had less education could receive some compensation for the disadvantages they faced during their childhood.

The previous argument is made at the conceptual level. Its implementation in the public policy arena requires taking into account other considerations such as the roles of information, incentives and targeting. For example, it can be discussed whether a high-income individual should also be compensated if he/she experienced early disadvantages in life.

From a more pragmatic point of view, some initiatives that have been advanced to improve the income distribution in the country, like those that originated in the Consejo de Trabajo and Equidad (2008), can be related to the issues of compensation and redressing, in addition to more traditional arguments.

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Appendix

Table 1A: Inequality results men 30 to 49 years old

Income	Wage Inequality		Inequality of opportunities		Share	
	GE(0)	GE(1)	GE(0)	GE(1)	GE(0)	GE(1)
Seven-year	0,220	0,252	0,046	0,052	0,208	0,206
	(0,011)	(0,014)	(0,007)	(0,011)	(0,027)	(0,041)
Four-year	0,239	0,274	0,046	0,050	0,191	0,184
	(0,012)	(0,016)	(0,007)	(0,011)	(0,028)	(0,041)
Yearly	0,263	0,300	0,046	0,050	0,176	0,166
	(0,013)	(0,017)	(0,007)	(0,012)	(0,027)	(0,042)
Monthly	0,264	0,301	0,046	0,049	0,175	0,164
	(0,013)	(0,017)	(0,007)	(0,012)	(0,027)	(0,041)

Notes: Seven-year income measure is the average wage from 2002 to 2008. Four-year income is the average wage from 2005 to 2008. Yearly income measured is the wage average for 2008, and monthly wage is the wage during June 2008. Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration.

Table 2A: Inequality results men 25 to 54 years old

	Wage Inequality		Inequality of opportunities		Share	
	GE(0)	GE(1)	GE(0)	GE(1)	GE(0)	GE(1)
Seven-year	0,218	0,252	0,038	0,044	0,176	0,176
	(0,010)	(0,014)	(0,005)	(0,008)	(0,020)	(0,027)
Four-year	0,239	0,277	0,038	0,043	0,160	0,154
	(0,011)	(0,015)	(0,005)	(0,008)	(0,020)	(0,029)
Yearly	0,263	0,302	0,038	0,041	0,145	0,136
	(0,012)	(0,016)	(0,006)	(0,009)	(0,020)	(0,029)
Monthly	0,264	0,303	0,038	0,041	0,144	0,134
	(0,012)	(0,016)	(0,006)	(0,009)	(0,020)	(0,029)

Notes: Seven-year income measure is the average wage from 2002 to 2008. Four-year income is the average wage from 2005 to 2008. Yearly income measured is the wage average for 2008, and monthly wage is the wage during June 2008. Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration.

Table 3A: Analysis by circumstance males between 25 to 54 years old

Income Measure	Father's Occupation	Mother's Education	Father´s Education	Region	Number of Siblings
	GE(1)	GE(1)	GE(1)	GE(1)	GE(1)
Seven-year	0,025	0,077	0,097	0,012	0,027
	(0,006)	(0,012)	(0,015)	(0,008)	(0,005)
Four-year	0,020	0,066	0,090	0,009	0,023
	(0,005)	(0,012)	(0,016)	(0,008)	(0,005)
Yearly	0,016	0,063	0,082	0,006	0,020
	(0,005)	(0,012)	(0,016)	(0,007)	(0,005)
Monthly	0,016	0,063	0,081	0,006	0,020
	(0,005)	(0,012)	(0,016)	(0,008)	(0,005)

Notes: Seven-year income measure is the average wage from 2002 to 2008. Four-year income is the average wage from 2005 to 2008. Yearly income measured is the wage average for 2008, and monthly wage is the wage during June 2008. Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration.

Table 4A: Regression Results, Males 30 to 49

	Seven-year	Four-year	Yearly	Monthly
Father`s Occupation	0.127	0.127	0.122	0.122
	(0.045)**	(0.048)**	(0.051)*	(0.051)*
Father`s Education	0.028	0.028	0.028	0.028
	(0.004)**	(0.004)**	(0.004)**	(0.004)**
Mother`s Education	0.024	0.026	0.027	0.027
	(0.004)**	(0.004)**	(0.004)**	(0.004)**
South	-0.158	-0.144	-0.129	-0.132
	(0.037)**	(0.039)**	(0.042)**	(0.042)**
North	-0.211	-0.207	-0.212	-0.214
	(0.032)**	(0.034)**	(0.036)**	(0.036)**
Number of Siblings	-0.020	-0.018	-0.017	-0.017
	(0.005)**	(0.005)**	(0.006)**	(0.006)**
Constant	12.343	12.392	12.403	12.404
	(0.038)**	(0.040)**	(0.043)**	(0.043)**
Observations	1611	1611	1611	1611
R-squared	0.20	0.19	0.17	0.17

Standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 5A: Regression Results, Males 25 to 54

	Seven-year	Four-year	Yearly	Monthly
Father's Occupation	0.111	0.106	0.098	0.098
	(0.041)**	(0.043)*	(0.046)*	(0.046)*
Father`s Education	0.024	0.024	0.024	0.024
	(0.003)**	(0.003)**	(0.004)**	(0.004)**
Mother`s Education	0.025	0.026	0.027	0.027
	(0.004)**	(0.004)**	(0.004)**	(0.004)**
South	-0.127	-0.125	-0.113	-0.115
	(0.033)**	(0.034)**	(0.036)**	(0.037)**
North	-0.157	-0.154	-0.155	-0.156
	(0.028)**	(0.030)**	(0.032)**	(0.032)**
Number of Siblings	-0.018	-0.018	-0.017	-0.017
	(0.004)**	(0.005)**	(0.005)**	(0.005)**
Constant	12.307	12.368	12.378	12.379
	(0.033)**	(0.035)**	(0.038)**	(0.038)**
Observations	2128	2128	2128	2128
R-squared	0.17	0.16	0.14	0.14

Standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 6A: Monte Carlo exercise, iid error term and no correlation between *f* and circumstances

Income Measure	Wage Inequality		Inequality of Opportunity		Share	
	GE0	GE1	GE0	GE1	GE0	GE1
Seven-year	0,227	0,221	0,027	0,026	0,121	0,119
	(0,008)	(0,008)	(0,003)	(0,004)	(0,013)	(0,014)
Four-year	0,226	0,220	0,028	0,026	0,122	0,120
	(0,007)	(0,007)	(0,003)	(0,004)	(0,013)	(0,015)
Yearly	0,228	0,222	0,027	0,026	0,118	0,116
	(0,007)	(0,007)	(0,003)	(0,004)	(0,012)	(0,015)
Monthly	0,250	0,245	0,028	0,026	0,111	0,106
	(0,008)	(0,009)	(0,004)	(0,005)	(0,014)	(0,017)

Note: Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration.

Table 7A: Monte Carlo exercise, iid error term with correlation between *f* and circumstances

Income Measure	Wage Inequality		Inequality of Opportunity		Share	
	GE0	GE1	GE0	GE1	GE0	GE1
Seven-year	0,222	0,219	0,028	0,029	0,126	0,131
	(0,008)	(0,009)	(0,003)	(0,004)	(0,015)	(0,018)
Four-year	0,222	0,220	0,028	0,028	0,125	0,129
	(0,008)	(0,010)	(0,003)	(0,004)	(0,012)	(0,016)
Yearly	0,223	0,222	0,028	0,029	0,124	0,129
	(0,008)	(0,010)	(0,003)	(0,004)	(0,014)	(0,018)
Monthly	0,241	0,237	0,028	0,027	0,114	0,115
	(0,008)	(0,010)	(0,004)	(0,005)	(0,015)	(0,020)

Note: Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration

Table 8A: Monte Carlo exercise, AR(1) error term with no correlation between *f* and circumstances

Income Measure	Wage Inequality		Inequality of Opportunity		Share	
	GE0	GE1	GE0	GE1	GE0	GE1
Seven-year	0,229	0,223	0,027	0,026	0,119	0,118
	(0,008)	(0,008)	(0,003)	(0,004)	(0,013)	(0,015)
Four-year	0,230	0,224	0,028	0,026	0,120	0,118
	(0,007)	(0,007)	(0,003)	(0,004)	(0,013)	(0,015)
Yearly	0,238	0,231	0,025	0,023	0,105	0,100
	(0,007)	(0,008)	(0,003)	(0,004)	(0,013)	(0,016)
Monthly	0,252	0,246	0,026	0,023	0,102	0,093
	(0,008)	(0,008)	(0,004)	(0,004)	(0,014)	(0,016)

Note: Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration

Table 9A: Monte Carlo exercise, AR(1) error term with correlation between *f* and circumstances

Income Measure	Wage Inequality		Inequality of Opportunity		Share	
	GE0	GE1	GE0	GE1	GE0	GE1
Seven-year	0,224	0,221	0,027	0,028	0,121	0,125
	(0,008)	(0,009)	(0,003)	(0,004)	(0,014)	(0,018)
Four-year	0,226	0,223	0,027	0,027	0,118	0,121
	(0,008)	(0,009)	(0,003)	(0,004)	(0,013)	(0,017)
Yearly	0,234	0,232	0,026	0,027	0,113	0,118
	(0,008)	(0,010)	(0,003)	(0,004)	(0,013)	(0,017)
Monthly	0,249	0,244	0,026	0,026	0,105	0,108
	(0,008)	(0,009)	(0,004)	(0,004)	(0,014)	(0,017)

Note: Standard error in parenthesis, calculated using 200 bootstrap repetitions. Own elaboration