

Changes over time in parental education and inequality of opportunities in Chile

Abstract:

We attempt to incorporate into the analysis of the inequality of opportunities the effect of changes in circumstances over time, which are usually approximated by parental education or occupation. We raise this issue because parents' circumstances change dramatically in a society where schooling patterns change rapidly, and we claim that the relative level of parental schooling is a better measure than the absolute level of education, which is generally used. We propose to control for parental cohorts of education for a given father's age to solve the problem empirically. We also test the sensitivity of the results under the ex-ante or the ex-post approaches to measure opportunity inequality.

JEL codes: D31, D63, H24, J60

Keywords: social mobility; inequality; income distribution.

I. Introduction

Recent studies claim that the concept of economic inequality is a broad concept that includes inequality stemming from two different sources: income inequality due to circumstances and inequality derived from effort. These two sources of inequalities are different in nature and merit opposite treatments from the theory of justice (Roemer, 1998). Inequality of opportunity is inequality due to circumstances and should ethically account negatively to the evaluation of social welfare because it is not of one's own responsibility. On the other hand, the source of inequality due to effort (the one that is due to individual responsibility) is outside the scope of compensation. Society should pursue and try to compensate for the first source of inequality and ignore the second component.

Many attempts have been made to break down these two sources of inequality in the literature. In this paper, we examine two alternative proposals: the approach proposed by Roemer (1993, 1998), followed, among others, by Ruiz Castillo (2003) and Peragine (2004), which is called the ex-post approach in the literature (we shall call it the within-tranches approach in this paper), and the so-called ex-ante approach postulated by Van de Gaer (1993) and Kranich (1996) (we shall call it the between-types approach). It has been shown that these two types of analyses are essentially different, both in theory, as shown by Fleubaey and Peragine (2009) and empirically, as illustrated by Checchi and Peragine (2010). We also provide some insights into these differences and investigate the convergence of both methodologies as the number of tranches, or the number of equal-effort groups, tends toward one.

Empirically, it is shown from the EU-SILC dataset that for all of the countries in this survey, the within-tranches approach increases the level of inequality of opportunity. This is a unanimous result obtained for the 25 European countries in the analysis by Checchi and Peragine (2010). This may incline us to conclude that it is an absolute fact empirically. However, we illustrate that for Chile in 2009, this is not the case, raising the question of potential disparities in the essence of inequality of opportunities between countries that are structurally quite different.

We also raise the main issue of this paper, the fact that circumstances may change over time. Circumstances are typically captured by parental education or occupation; this is the case in most of the empirical works (see for instance Roemer et al. (2003), Bourguignon et al. (2007), Lefranc et al. (2008), Rodriguez (2008), Pistoiesi (2009) and Checchi and Peragine (2010)). In this paper we address the issue of how circumstances, measured by parents' education, may vary in time, following a historical trend in which schooling attainments have increased steadily

over time, as is clear from the increasing rates of secondary and tertiary education in the population.

This may cause a problem because the value of parental education may not be the same for all individuals at a moment in time. The relative importance of tertiary or secondary parental education varies, and it may not have the same relative value for different age cohorts in a given year. We claim in this paper that it is the relative importance of parental schooling that matters for access to labor markets and is relevant to define circumstances. We will try to correct for this issue and attempt to homogenize circumstances by using a time-adjusted variable for parents' education. We illustrate the significance of the bias due to failing to adjust for this issue, using data from Chile in 2009.

II. Inequality of opportunity measurement

Assume the pragmatic approach to individual responsibility proposed by Roemer (1993). We must partition the entire population into equal circumstance subgroups or *types*. Let $\Omega = \{1, \dots, \nu\}$ be the set of all possible circumstances. Let us denote by $x_{\cdot\gamma} = \{x_{1\gamma}, \dots, x_{n_\gamma\gamma}\} \in \mathbb{R}_{++}^{n_\gamma}$ the increasingly ordered subgroup income vector for circumstance γ , where $\gamma \in \{1, \dots, \nu\}$. The population of this type is composed of n_γ individuals.

The entire population can then be represented by the income vector $x = \{x_{\cdot 1}, \dots, x_{\cdot \nu}\} \in \mathbb{R}_{++}^n$, according to this partition. The entire population is composed of n individuals:

$$n = \sum_{\gamma=1}^{\nu} n_\gamma.$$

Let us define $\bar{x}_{\cdot\gamma}$ as the arithmetic mean of the γ -subgroup income vector:

$$\bar{x}_{\cdot\gamma} = \sum_{i=1}^{n_\gamma} \frac{x_{i\gamma}}{n_\gamma}.$$

Now we define the subgroups with the same responsibility/effort so as to partition the whole population into equal effort groups or *tranches* (sets of individuals with the same effort). Let us define the γ th-subgroup cumulative frequency distribution function, $F_\gamma(\cdot)$; by $F_\gamma^{-1}: [0,1] \rightarrow \mathbb{R}_+$ we denote $F_\gamma^{-1}(p) = \inf\{x: F_\gamma(x) \geq p\}$, the left continuous inverse subgroup ranked in the percentile $p = \frac{i}{n_\gamma}$.

Let us define the level of effort of individuals across circumstance subgroups according to the following assumption of “statistical solution” made by Roemer:

$$\text{Let } e_{i\gamma} \geq e_{j\delta} \Leftrightarrow F_{\gamma}(x_{i\gamma}) \geq F_{\delta}(x_{j\delta}).$$

Individuals with different circumstances are assumed to have exerted the same effort if they are in the same percentile in the income distributions of their own circumstances.

We then define the partition of tranches according to all possible efforts. If all types were equally populated, say $n_1 = \dots = n_{\nu} (= n_{\gamma})$, then the equal responsibility subgroups or tranches are defined according to the set of efforts $E = \{e_1, \dots, e_{n_{\gamma}}\}$. Therefore, we define, for a given effort k , the k th-equally-responsible subgroup income vector $x_k = \{x_{k1}, \dots, x_{k\nu}\} \in \mathbb{R}_{++}^{\nu}$, where $k \in \{1, \dots, n_{\gamma}\}$. Note that $x_k = \{F_1^{-1}(k/n_{\gamma}), \dots, F_{\nu}^{-1}(k/n_{\gamma})\} \in \mathbb{R}_{++}^{\nu}$.

Let us denote by \bar{x}_k as the arithmetic mean of the k th-equally-responsible subgroup income vector:

$$\bar{x}_k = \sum_{\gamma=1}^{\nu} \frac{x_{k\gamma}}{\nu}.$$

If all types were not equally populated and if we are interested in getting smoother results, we can proceed by assuming a grouped partition by effort quantiles $E_q = \{e_1, \dots, e_q\}$, where each subgroup includes n_{γ}/q individuals ranked increasingly according to their income levels for each circumstance γ . For example, we can consider centiles of effort, in which q equals 100, or deciles, in which $q = 10$. Then we define an equally-responsible subgroup with the same effort in the quantile j as $\bar{x}_j = \{\bar{x}_{j1}, \dots, \bar{x}_{j\nu}\} \in \mathbb{R}_{++}^{\nu}$, where $\bar{x}_{j\gamma}$ is the quantile mean for circumstance γ , for all $j \in \{1, \dots, q\}$ and $\gamma \in \{1, \dots, \nu\}$.

We can define the inequality of opportunities according to two main approaches:

1. Between-types inequality, proposed by Van de Gaert, (1993) and Kranich (1996), it is also called the ex-ante approach. The null-inequality of opportunity benchmark is defined as the circumstance in which there is no inequality among different types. The inequality of opportunity increases with the between-types inequality, defined as the inequality index of the hypothetical distribution that assigns to everyone in the same type the mean-type income,

$$I_{TY}^B = I(\bar{x}_{.1}, \dots, \bar{x}_{.\nu}).$$

It is normally used an additive decomposable class of indices, such as the generalized entropy family, so the total inequality can be written as

$$I(x) = I_{TY}^B + I_{TY}^W = I(\bar{x}_{.1}, \dots, \bar{x}_{.v}) + I^W(x_{.1}, \dots, x_{.v}).$$

If the mean log deviation is used, population share weights apply, and we can write

$$I_{TY}^W = I^W(x_{.1}, \dots, x_{.v}) = \sum_{\gamma=1}^v I(x_{. \gamma})/n_{\gamma}.$$

2. Within-tranches inequality, also called the ex-post approach proposed by Roemer (1993, 1998) and followed, among others, by Ruiz Castillo, (2003) and Peragine (2004). The null-inequality of opportunity benchmark exists when, after controlling for equal efforts, there is no inequality among different tranches. The higher the within-tranches inequality, the higher the inequality of opportunity:

$$I_{TR}^W = I^W(x_{.1}, \dots, x_{n_{\gamma}}) = f[I(x_{.1}), \dots, I(x_{n_{\gamma}})].$$

If the mean log deviation is used, we again have population share weights to aggregate the index. Then, for the quantile analysis, we can write

$$I_{TR}^W(q) = I^W(x_{.1}, \dots, x_{.q}) = \sum_{j=1}^q I(x_{.j})/q,$$

and the total inequality can be written as

$$I(\bar{x}_{..}) = I_{TR}^B(q) + I_{TR}^W(q) = I(\bar{x}_{.1}, \dots, \bar{x}_{.q}) + \sum_{j=1}^q I(x_{.j})/q,$$

where $\bar{x}_{..}$ is the matrix of $\bar{x}_{j\gamma}$ for all $j \in \{1, \dots, q\}$ and $\gamma \in \{1, \dots, v\}$.

We compute this index for several values of q, and eventually the values converge to the Van de Gaert analysis as q tends to 1.

$$I_{TR}^W(q = 1) = I_{TY}^B = I(\bar{x}_{.1}, \dots, \bar{x}_{.v})$$

Although in theory there is no clear convergence path, that is, the sign of $\frac{\Delta I_{TR}^W(q)}{\Delta q}$ is uncertain

(see, for instance, Fleubaey and Peragine (2009)), we will show that in practice it is not a decreasing monotone path.

An example: For the $q = 2$ and $\nu = 2$ case,

we can show that $I_{TR}^W(q = 2) \begin{matrix} \leq \\ \geq \end{matrix} I_{TR}^W(q = 1) = I_{TY}^B$.

Let us consider an example with three distributions with the same I_{TY}^B , that is, with the same mean income for the two types, say $\bar{x}_1 = 15$ and $\bar{x}_2 = 45$, for the low and high parental education levels, respectively. Assume without loss of generality that the subgroups have equal populations.

Distribution 1, for $q = 2$, is given by $\bar{x}_1 = (10, 30)$ for the poorest 50% tranche and $\bar{x}_2 = (20, 60)$ for the richest 50% tranche. Because we are considering relative inequality indices, $I(\bar{x}_1) = I(\bar{x}_2) = I_{TY}^B(\bar{x}_1, \bar{x}_2)$. Thus, in this case, we have $I_{TR}^W(q = 2) = I_{TR}^W(q = 1) = I_{TY}^B$. The mean log deviation attains a value of 0.1438.

Distribution 2 is given by $\bar{x}_1 = (15, 30)$ for the first tranche and $\bar{x}_2 = (15, 60)$ for the second tranche, derived from a progressive transfer within the “adverse-circumstances” type, so $I_{TR}^W(q = 1) = I_{TY}^B = 0.1438$ is unchanged from the reference distribution 1. However, $I(\bar{x}_1)$ is decreased to 0.0589 in the first tranche, and $I(\bar{x}_2)$ is increased to 0.2231 in the second tranche. Thus, the average is lower than the reference:

$$I_{TR}^W(q = 2) = \sum_{j=1}^2 I(\bar{x}_j) / 2 = 0,1410.$$

Thus, $I_{TR}^W(q = 2) < I_{TR}^W(q = 1) = I_{TY}^B$.

Finally, we have distribution 3, given by $\bar{x}_1 = (10, 45)$ for the poorest 50% tranche and $\bar{x}_2 = (20, 45)$ for the richest 50% tranche, which is derived from a progressive transfer within the “good-circumstances” type, so $I_{TR}^W(q = 1) = I_{TY}^B = 0.1438$ is unchanged from the reference distribution 1. In this case, $I(\bar{x}_1)$ is increased to 0.2596 in the first tranche, and $I(\bar{x}_2)$ is increased to 0.08 in the second tranche. Thus, the average is higher than the reference:

$$I_{TR}^W(q = 2) = \sum_{j=1}^2 I(\bar{x}_j) / 2 = 0,1698.$$

So, $I_{TR}^W(q = 2) > I_{TR}^W(q = 1) = I_{TY}^B$.

How can the sign of $\frac{\Delta I_{TR}^W(q)}{\Delta q}$ be uncertain? We have the intuition that if the number of tranches q increases, then the inequality should increase. The answer is that the overall inequality is increasing in q : $I_{TY}(q) = I_{TY}^B + I_{TY}^W(q) = I_{TR}(q) = I_{TR}^B(q) + I_{TR}^W(q)$. Then, in incremental terms, we have

$$\frac{\Delta I_{TR}(q)}{\Delta q} = \frac{\Delta I_{TY}(q)}{\Delta q} = \frac{\Delta I_{TY}^W(q)}{\Delta q} \geq 0. \text{ Note that } \frac{\Delta I_{TY}^B(q)}{\Delta q} = 0, \text{ because it does not depend on } q.$$

We also have $\frac{\Delta I_{TR}^B(q)}{\Delta q} \geq 0$, but the sign of $\frac{\Delta I_{TR}^W(q)}{\Delta q}$ is equal to that of $\frac{\Delta I_{TY}^W(q)}{\Delta q} - \frac{\Delta I_{TR}^B(q)}{\Delta q}$ and is uncertain.

A necessary and sufficient condition for $\frac{\Delta I_{TR}^W(q)}{\Delta q}$ to be negative is that $\frac{\Delta I_{TR}^B(q)}{\Delta q} \geq \frac{\Delta I_{TY}^W(q)}{\Delta q} \geq 0$. In other words, when passing from $q = 2$ tranches to $q = 1$ tranche analysis, the within-tranches inequality is increased if (and only if) the between-tranches inequality loss of combining the groups is sufficiently high and exceeds the starting within-types inequality. In the example above, in distribution 2, where $\frac{\Delta I_{TR}^W(q)}{\Delta q}$ is negative, we have in fact $I_{TR}^B(q = 2) = 0.0323 > I_{TY}^W(q = 2) = 0.0295$. Note that $I_{TR}^B(q = 1) = I_{TY}^W(q = 1) = 0$.

III. Database

In the empirical exercise, we have used the National Socioeconomic Characterization Survey (Caracterización Socioeconómica Nacional, CASEN). This survey constitutes the main source of information for the design and evaluation of economic policies in Chile. CASEN is a representative household survey at the national, regional, urban, rural and communal levels. It was first implemented in 1985. In our empirical exercise, we have used the last available wave, corresponding to 2009.

This survey provides information about the socioeconomic conditions of the different social sectors of the country and the distribution and composition of household incomes, as well as the incidence, magnitude and characteristics of poverty. It also contains information regarding the coverage and profile of the recipients of social programs.

The survey has the following modules:

1. Residents: type of dwelling, head of household's profile

2. Education: illiteracy, schooling, parental education
3. Employment: relationship with activity, working hours, unemployment, wage rate
4. Income: poverty incidence, type of income, social benefits
5. Health: health care, frequency of disease, coverage of social security systems
6. Housing: type of dwelling, housing problems, equipment, housing programs

We have focused on the personal labor income distribution among male heads of household and, as discussed below, most of the analysis has been conducted by restricting the sample to 30 to 50 year old employees.

IV. Empirical exercise

The empirical exercise was conducted using the last wave of CASEN, i.e., for Chile in 2009. We have considered two circumstances to partition the population: ethnic group and father's education. With regard to racial classification, we have considered two groups: indigenous people and others. In Chile, the law recognizes the existence of nine indigenous groups, among which the most important are the Aymara and the Mapuche people. As can be observed in Table 1, they represent about ten percent of the sample, and their average labor income is significantly lower than that of non-indigenous people.

Table 1 Average labor income (total sample)

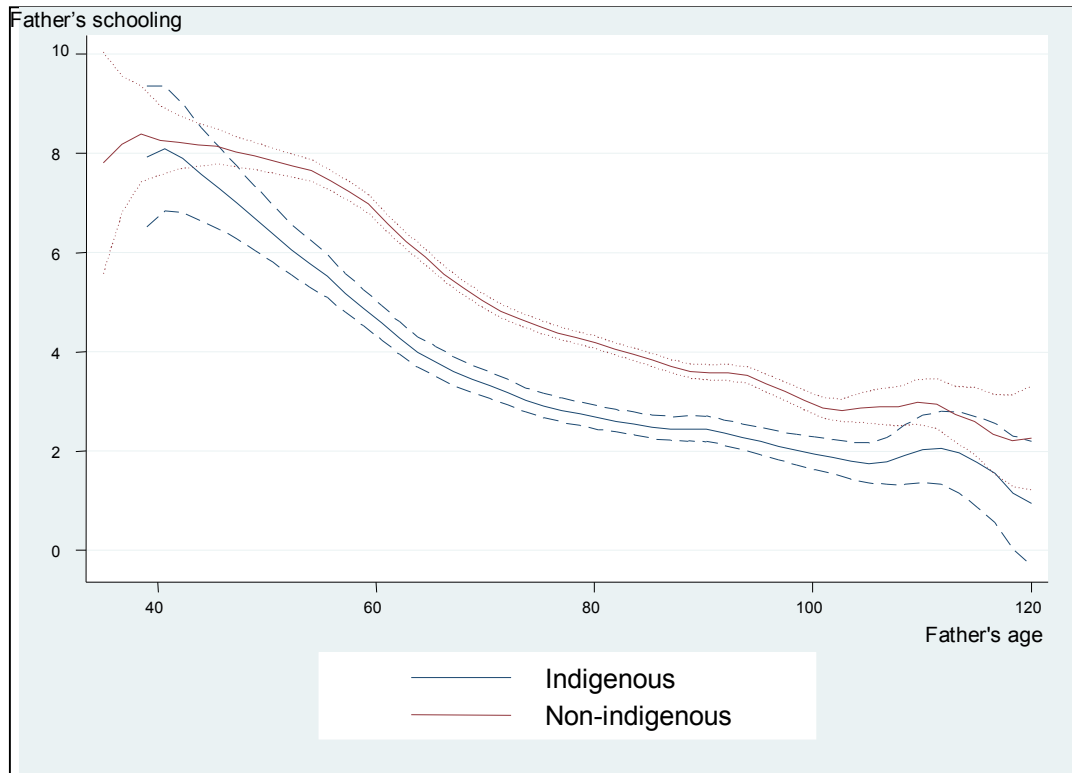
	N. observations	Mean	Std. Err.
Non-indigenous	18944	487271.26	5572.333
Indigenous people	2120	359367.55	9402.326
Total	21064	474398.3	5106.9
Difference		127903.7	10929.53
T-test (Ho: diff = 0)		11.7026	

Note: Figures refer to male employees, heads of household between 20 and 65 years old.

The second circumstance considered is the father's education. In analyzing this variable, we should take into account the fact that it has tended to increase over time. As in other countries, schooling has increased in Chile very rapidly in the last few decades, and it may be an error to equate individuals with parents who have the same years of schooling if their ages differ. For instance, secondary education for older cohorts of fathers could be equivalent to low-university education among younger cohorts. Similarly, individuals with fathers with less than primary

education could have a worse starting point now than thirty years ago. The circumstances of access to the labor market have changed over time. Let us illustrate this point in greater detail.

Figure 1. Father's years of schooling vs. father's (potential) age in 2009



We have applied nonparametric techniques to smooth the relationship between fathers' years of schooling and their ages. In particular, we have used the Nadaraya-Watson nonparametric smoother (Nadaraya, 1964 and Watson, 1964) with the Epanechnikov kernel (Epanechnikov, 1969). In Figure 1, we show the evolution for both indigenous and non-indigenous people. The dotted and dashed lines delimit the 95 percent confidence intervals. It is clear that the older the father, the lower his schooling attainment. The differences between the two ethnic groups are also significant, with the indigenous being the least favored group in terms of schooling. However, these differences have been reduced in recent years, so that among individuals whose parents are younger than fifty years old, the differences are not significant according to the correspondent t-test.

We have tried to take into account this pattern to define homogeneous circumstance by using a time-adjusted variable for the father's education. Fathers' levels of schooling were compared exclusively with people in the father's age group, that is, those males within an interval of ± 5 years of age. Consequently, each father was compared with those individuals who entered the

labor market at approximately the same time and were competing with him in terms of jobs, occupations and wage rates. Individuals were classified into quartiles based on their fathers' years of schooling within these ± 5 years of age intervals. In order to compare our results to the traditional approach, we have restricted the sample to the employees between 30 and 50 (i.e., the fathers' age is restricted to the central years of the life cycle (30-50)).

Furthermore, we also defined fathers' education quartiles without controlling for the cohort effect. Table 2 compares the two ways to classify the sample. It can be observed that most of the discrepancies correspond to observations below the principal diagonal, that is, observations ranked in a lower quartile when the cohort effect is considered. Because these observations correspond to younger fathers, if we do not take into account changes in the average schooling over time, we could be overvaluing the real circumstances of the younger cohorts.

Table 2. Quartiles of father's years of schooling

Whole distribution	Controlling for the cohort effect			
	Q1	Q2	Q3	Q4
Q1	3301 (77.3)	--	--	--
Q2	557 (61.2)	2452 (73.9)	706 (85.7)	2 (1170)
Q3		464 (57.2)	1900 (71.1)	382 (86.1)
Q4		--	394 (56.5)	2195 (71.6)

Note: Average father's age in brackets

1. *Between-types inequality*

We first present the between-types inequality by the mean log deviation of the types defined by the quartiles of father's education and the ethnic groups in Table 3. We compute the Shapley value to isolate the contribution of each circumstance separately. Because both marginal effects may depend on the order of the decomposition (that is, if we compute first the father's education effect and second the ethnicity effect or vice versa), we calculate the Shapley value that does not depend on the order employed. We observe that the total and education inequality of opportunity is lower when the cohort effect is taken into account (that is, the between-groups inequality of opportunity decreases after controlling for changes in education over time). However, we also compute the inequality of opportunities due to ethnicity, which is larger when the father's cohort effect is taken into account. This result may be due to the fact that ethnicity is a marginal component of the total inequality. Nonetheless, because both circumstances are highly correlated, and being a member of the indigenous people was associated with lower

schooling attainments until recent times, ethnicity is also a relevant cause that indirectly affects inequality of opportunities through low parental education.

Table 3. Shapley values of between-types inequality

	No cohort effect	Cohort effect
Ethnicity	0.0018	0.0019
Fathers' schooling	0.0524	0.0517
Total between-types ineq.	0.0542	0.0536
Total inequality	0.4005	

2. *Within-tranches inequality:*

In Table 4, we extend the analysis to the within-tranches inequality, and we find that far from increasing the measure of the inequality of opportunities compared with the between-types inequality approach, as happened in the European countries, it reduces it. When each of the eight groups defined by ethnicity and father's schooling is, in turn, split into more income quartiles, the total within-tranches inequality index tends to drop if the cohort effect is taken into account (see also Figure 2).

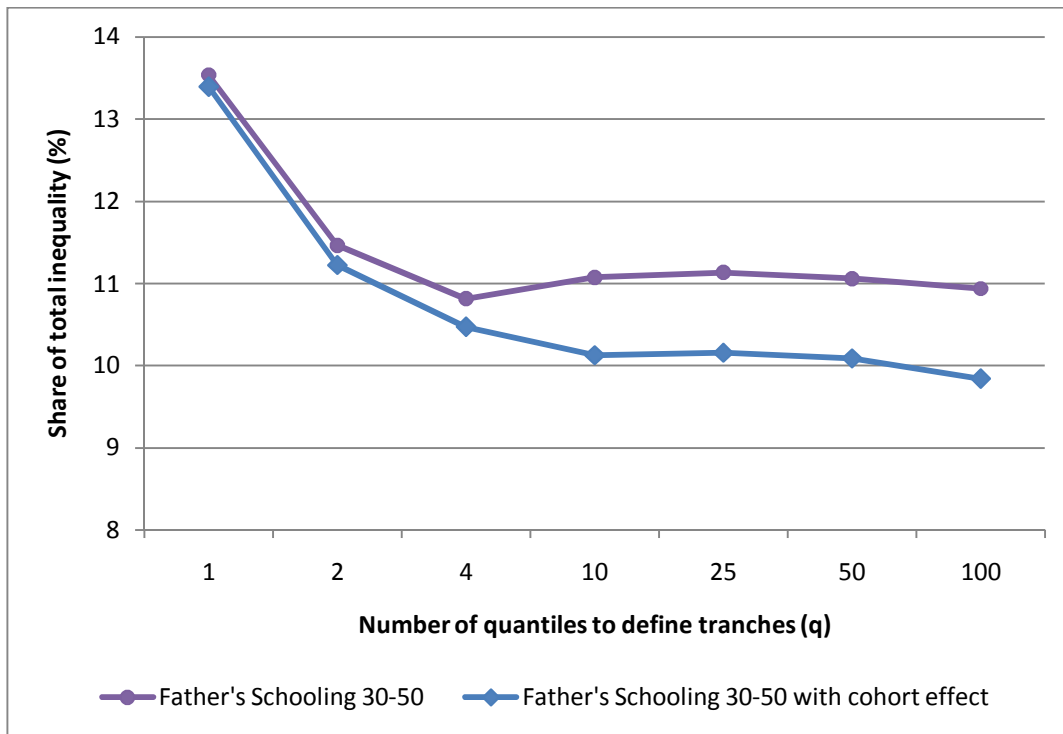
Table 4. Shapley values of within-tranches inequality

# quantiles to define tranches	2		4		10		100	
	No Cohort Effect	Cohort Effect	No Cohort Effect	Cohort Effect	No Cohort Effect	Cohort Effect	No Cohort Effect	Cohort Effect
Ethnicity	0.0012	0.0020	0.0023	0.0029	0.0022	0.0029	0.0032	0.0030
Father's schooling	0.0447	0.0429	0.0410	0.0391	0.0421	0.0376	0.0406	0.0364
Total within-tranches ineq.	0.0459	0.0449	0.0433	0.0419	0.0443	0.0405	0.0438	0.0394
Total inequality	0.4005							

Moreover, the cohort effect remains negative for all numbers of tranches or equal-effort groups, (i.e., controlling for the average education changes over time leads to smaller estimations of the within-tranches inequality, with respect to the between-types inequality). Figure 2 shows the evolution of the share of total inequality due to the within-tranches inequality as the number of income quantiles considered increases. It can be observed that the general pattern is similar with and without controlling for the fathers' cohort effect on education, but, as mentioned above, the measure of the inequality of opportunities is lower if we control for the cohort effect, and this difference grows as we increase the number of tranches. These changes are related to the

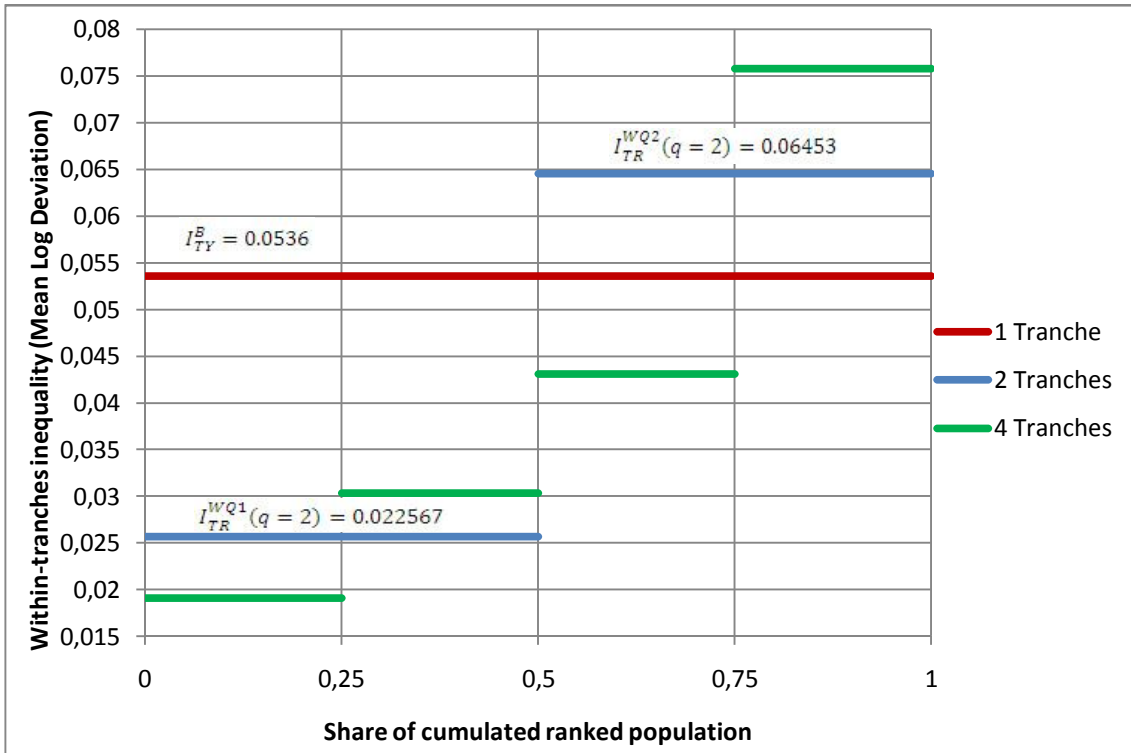
reassignments of people between father's education quartiles when the cohort effect is taken into consideration. The net effect moves relatively young and poor people of a given father's schooling quartile to a lower educational quartile, where they become relatively rich (see Table 2), and wealthier groups thus lose their relatively poorer members, so the average income of the upper quartiles rises.

Figure 2. Total within-tranches inequality of opportunity



Returning to the general result, the within-tranches inequality is lower than the between-types inequality regardless of the number of income quantile groups to define tranches. This is not a common result in the literature, especially when the inequality of opportunities has been estimated using developed countries (Checchi and Peragine, 2010). Therefore, in Figure 3, we try to explain this result by presenting the within-tranches inequality by ordered tranches. This figure displays the effect of passing from 1 tranche (i.e., the between-groups analysis) to 2 tranches and eventually to quartiles (4 tranches).

Figure 3. Total within-tranches inequality disaggregation (1 to 4 tranches)



As in the example in Section 2, we have the 1 tranche result ($q = 1$ case) on the red line: $I_{TR}^W(q = 1) = I_{TY}^B = 0.0536$

For the two-tranches case (blue lines), we have

$$I_{TR}^W(q = 2) = \sum_{j=1}^2 I(\bar{x}_j)/2 = (0.022567 + 0.06453)/2 = 0.04494,$$

which is lower than the result for 1 tranche, due to the very low value of the first of the two tranches. Furthermore, moving to four tranches, it is clear from Figure 3 that the first two quartiles have a lower average index than that for the first half of the distribution. Correspondingly, the last two quartiles also have an average index below the index of the second half of the distribution. Therefore, again, the inequality of opportunities index for 4 tranches (green lines) is lower than that for 2 tranches. The extension to 10 or even 100 tranches does not change the result when controlling for the father's cohort effect, and therefore, the within-tranches inequality of opportunities decreases in this case but not monotonically as the number of tranches increases.

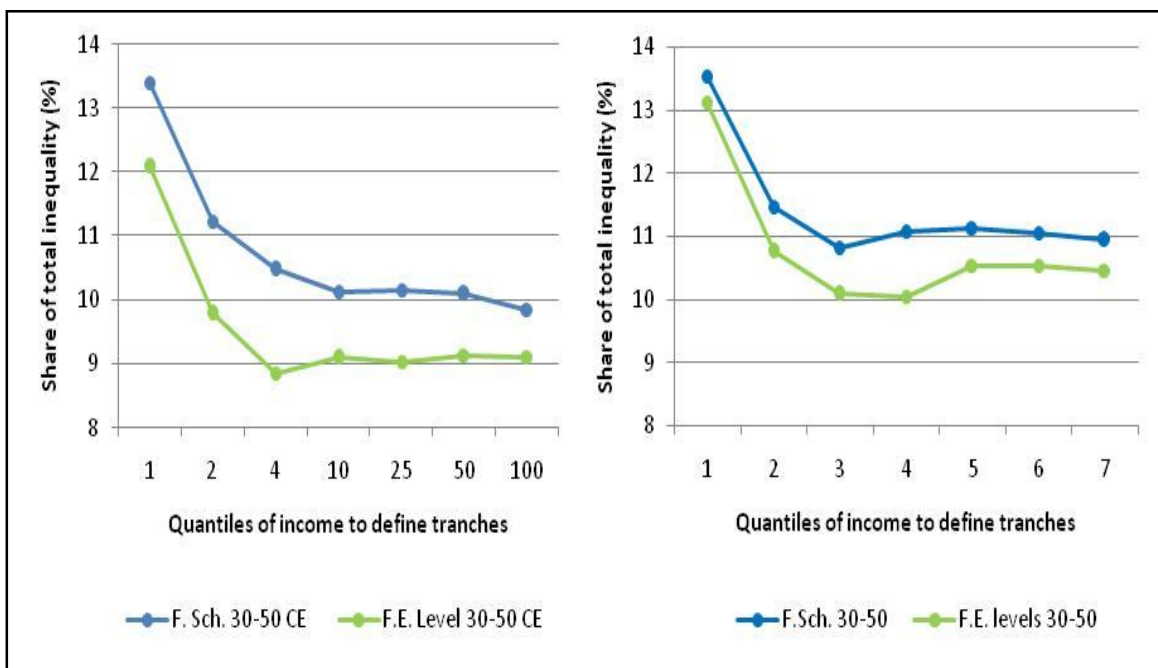
It may be interesting to determine the sensitivity of the results to the definition of the education variable and to the selected sample age. The next section deals with these issues.

V. Extensions

Schooling effect

We have tried to check the robustness of our results by using a more conventional definition of circumstances, using, instead of the father's years of schooling, the father's educational level controlled for the cohort effect.¹ It can be observed, in Figure 4, that the definition of the circumstances does affect the results significantly, although, when computed in terms of the father's schooling, the measure of the inequality of opportunities is relatively higher. In any case, Figure 4 also shows that the within-tranches inequality is lower than the between-types inequality regardless of how we define parental education. Therefore, it seems that this result is robust to the definition of circumstances.

Figure 4. Within-tranches inequality of opportunity according to alternative definitions of father's education

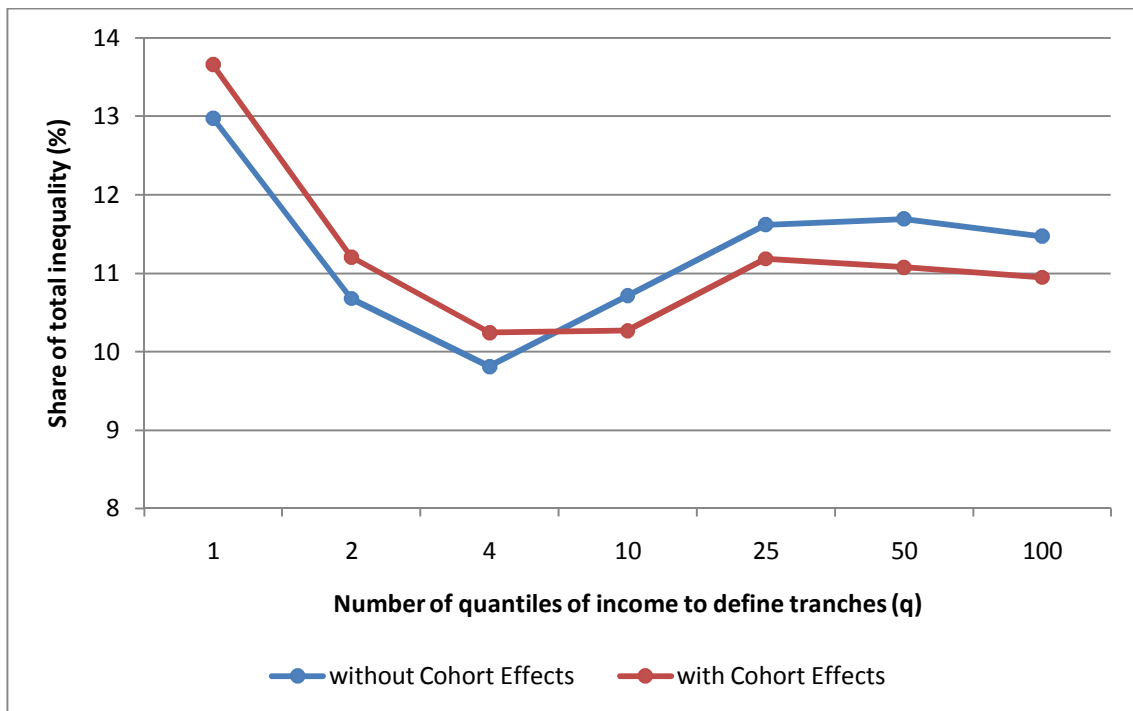


¹ Roemer et al. (2003) use a similar concept of parental schooling to that used in this paper, primarily defined by years of education and then sorted into categories.

The age effect

In order to check the extent to which the use of age constraints to define the sample affects the estimations of inequality of opportunities, we have compared our previous results with the estimates obtained with an alternative sample composed of all employees between 20 and 65 years old. Figure 5 shows the evolution of the share of total inequality due to the within-tranches inequality as the number of income quantiles considered increases for the extended sample. It can be observed that, again, the between-types inequality is higher than the within-tranches indices for both approaches. Additionally, the general pattern is similar regardless of whether the fathers' cohort effect is controlled, but both lines cross between four and ten percentiles, and the measure of the inequality of opportunities is lower if we control for the cohort effect only for a sufficiently large number of income quantiles.

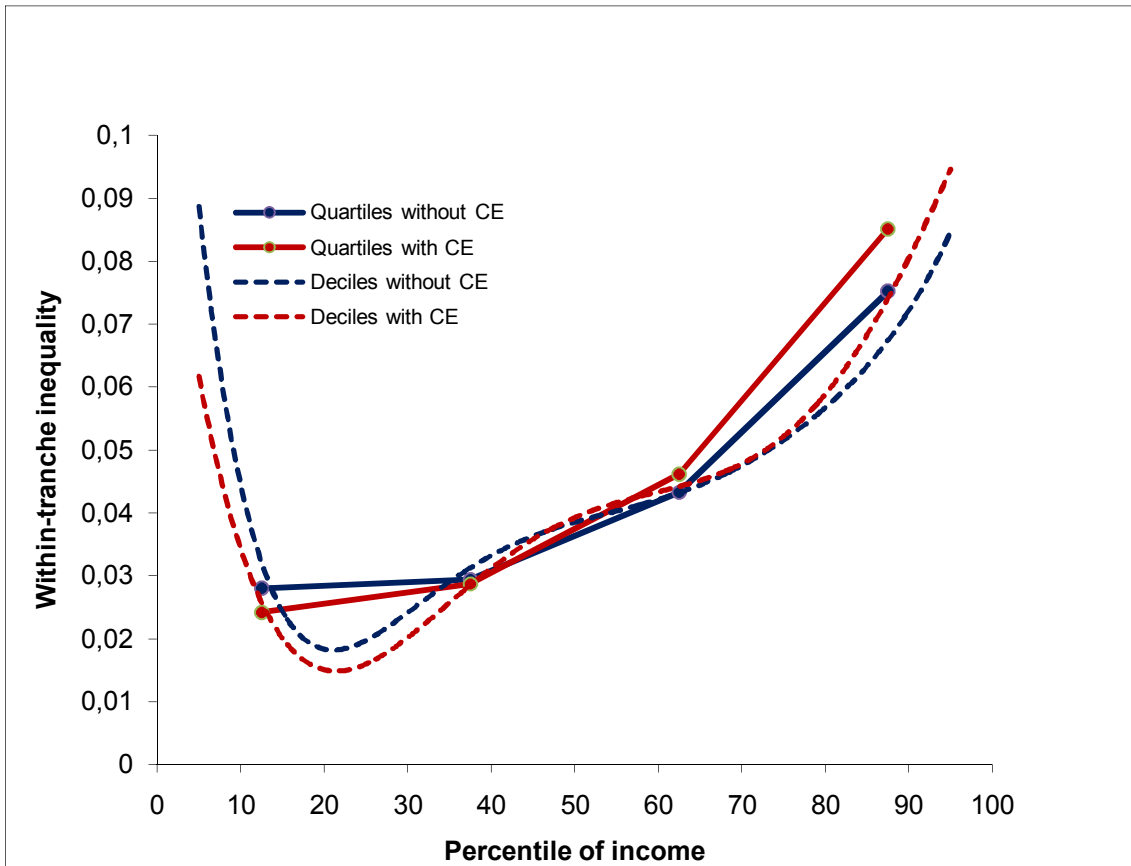
Figure 5. Total within-tranches inequality of opportunity among employees 20-65 years old



The reason why the cohort effect becomes positive for a small number of income tranches for the extended sample is investigated in Figure 6. In the first half of the eight income distributions defined by ethnicity and father's schooling, the cohort effect is negative (i.e., the estimated inequality of opportunities index is smaller when changes over time in fathers' schooling are taken into account when defining circumstances). However, it is positive for the upper tail of the income distribution. It seems that with a small number of income groups within each education

quartile, the lower tail has a larger impact on the estimated inequality of opportunities for the extended sample.²

Figure 6. Total within-tranches inequality with and without cohort effect among employees 20-65 years old (4 to 10 tranches)



The main reason for this pattern is that, when the changes over time in the father’s schooling are taken into consideration, in this extended sample the net effect moves many more relatively poor employees in a given father’s schooling quartile to a lower education quartile compared with the reassignments when the sample is restricted to employees aged 30-50. As stated in Table 5, the average income of the upper quartiles rises, but the average income of the first education quartile decreases after controlling for the changes over time. This expands the between-groups inequality, leading to a larger between-type inequality of opportunities index estimated with the cohort effect as well as a positive cohort effect for small numbers of tranches. It is true that all these reassignments also affect the within-type inequality, but with a

² For comparison purposes, Figure A1 at the Appendix reproduces this graphical analysis for the restricted sample (employees 30-50 years old).

small number of tranches, this component has a small impact on the overall measure of the within-tranches inequality of opportunities.

Table 5. Average labor income and within-tranches inequality by fathers' education quartiles (employees 20-65 years old)

	No Cohort Effect			Cohort Effect		
	Population share	Average Income	Mean log deviation	Population share	Average Income	Mean log deviation
Q1	0.293	333918	0.3878	0.328	333093	0.3704
Q2	0.209	362321	0.3569	0.230	380385	0.3382
Q3	0.298	469910	0.3674	0.246	471575	0.3717
Q4	0.199	805334	0.4644	0.195	827585	0.4922

In any case, the within-types inequality changes are not monotonous across quartiles. In the first two quartiles of fathers' schooling, the within-types inequality drops, whereas it increases in the upper quartiles, as can be observed in Table 5. Furthermore, these movements relatively raise the lower income quantiles of the more disadvantaged groups more, decreasing the within-tranches inequality in the lower part of the income distributions when the cohort effect is considered.

The shift in the cohort effect from positive to negative with the extended sample is related to the more stable measure of inequality when the sample is restricted to ages 30-50 years (Figure 7). Therefore, this can be understood as a potential advantage of constraining the sample to a more heterogeneous age group, at the very least for this application to Chilean data.

Figure 7. Within-tranches inequality of opportunity by alternative sample age



VI. Conclusions

In this paper, we have tried to incorporate into the analysis of the inequality of opportunities the effect of changes over time in average parental circumstances, which are usually approximated by parental education or occupation. Specifically, we have taken into account how fathers' schooling has increased over time. We have found a net effect that reallocates younger and relatively poorer people within a given father's schooling quartile to a lower education quartile. Therefore, if we do not take into account changes in the average schooling over time, we could over-value the real value of fathers' education for the youngest cohorts, because the historical trend of improving education has eroded the relative value of education for this group.

Overall, our empirical exercise shows the result that the cohort effect is negative, especially for the ex-post or within-tranches approach and for a large number of tranches.

We also performed a sensitivity analysis on the number of tranches taken into consideration. We observe that the Van der Gaer ex-ante approach (the limiting case when the number of tranches tends to 1) attains the maximum level of inequality of opportunity, despite studies for the UE economies that unanimously show the opposite result. Additionally, consideration of the parental cohort effect of schooling tends to reduce the measure of inequality of opportunities for the Roemer ex-post within-tranches analysis regardless of the way in which the father's education is assessed.

References

- Bourguignon, F., Ferreira, F. and Menéndez, M. (2007). "Inequality of opportunity in Brazil", *Review of Income and Wealth*, Vol. 53, pp. 585-618.
- Checchi, D. and Peragine, V. (2010). "Inequality of opportunity in Italy", *Journal of Economic Inequality*, Vol 8, pp.429-450.
- Fleurbaey, M. and Peragine, V. (2009). Ex ante versus ex post equality of opportunity, ECINEQ working paper Num.141.
- Epanechnikov, V.A. (1969). "Nonparametric Estimation of a Multivariate Probability Density", *Theory of Probability and Its Applications*, Vol.14, pp. 153-158.
- Lefranc, A., Pistoiesi, N. and Trannoy A. (2008). "Inequality of opportunities vs. inequality of outcomes: Are Western societies all alike?", *Review of Income and Wealth*, Vol. 54, pp. 513-546.
- Kranich, L. (1996). "Equitable opportunities: an axiomatic approach", *Journal of Economic Theory*, Vol. 71, pp. 131-147.
- Nadaraya, E. (1964). "On estimating regression", *Theory of Probability and its Applications*, Vol. 9, pp. 141-142.
- Peragine, V. (2004). Measuring and implementing equality of opportunity for income, *Social Choice Welfare*. Vol. 22(1), pp. 187-210
- Pistoiesi, N. (2009). "Inequality of opportunity in the land of opportunities, 1968-2001", *Journal of Economic Inequality*, Vol. 7, pp.411-433.
- Rodriguez, J. (2008). "Partial equality-of-opportunity orderings", *Social Choice and Welfare*, Vol. 31(3), pp. 435-456.
- Roemer J.E. (1993). "A pragmatic theory of responsibility for the egalitarian planner", *Philosophy and Public Affairs*, Vol. 22, pp. 146-166.
- Roemer J.E. (1998). Equality of Opportunity, Harvard: Harvard University Press.
- Roemer, J.E., Aaberge, R., Colombino, U., Fritzell, J., Jenkins, S., Marx, I., Page, M., Pommer, E., Ruiz-Castillo, J., San Segundo, M. J., Tranaes, T., Wagner, G. and Zubiri, I. (2003). "To what extent do fiscal regimes equalize opportunities for income acquisition among citizens?", *Journal of Public Economics*, Vol. 87, pp. 539-565.
- Ruiz-Castillo, J. (2003). The measurement of inequality of opportunities. In: Bishop, J., Amiel, Y. (eds.), *Research on Economic Inequality*, Vol. 9, pp. 1-34.
- Van de Gaer, D. (1993). "Equality of opportunity and investment in human capital", *Catholic University of Leuven*, Faculty of Economics, no. 92. Watson, G. S. (1964). "Smooth regression analysis," *Sankhya: The Indian Journal of Statistics, Series A*, Vol. 26, pp. 359-72.

Appendix

Figure A1. Total within-tranches inequality with and without cohort effect among 30-50 year old employees (4 to 10 tranches)

