Where You Are Born Matters

Inequality of Opportunities and Intergenerational Mobility across Colombia's Territory

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Abstract

The circumstances into which individuals are born are beyond their control, yet they play a significant role in shaping people's economic opportunities and are thus key drivers of inequality and its persistence over time. Understanding the role of place of birth is essential to understanding inequality of opportunities and social mobility, both of which directly affect overall inequality. This paper uses machine learning techniques and data from Colombia, one of the most unequal countries in Latin America and the Caribbean, to estimate inequality of opportunity and intergenerational education mobility indexes. The analysis incorporate place of birth and a more granular geographic lens to capture the extent of regional disparities. The findings show that 49 percent of the Gini income inequality is explained by circumstances at birth, and place of birth accounts for up to half of these inequalities. Intergenerational mobility measures at the department (province) level also reveal striking disparities in opportunities across the country. These findings underscore the critical role that place of birth plays in perpetuating inequality, providing important insights for policies aimed at promoting social mobility and reducing territorial disparities.

Where You Are Born Matters:
Inequality of Opportunities and Intergenerational Mobility across Colombia's Territory[1]

María Eugenia Dávalos[2] and Juan Manuel Monroy[3]

I. Introduction

Income inequality can be driven by factors within an individual's control, such as effort (Roemer, 1993). However, the stark reality contradicts a uniform landscape of opportunity, even under equal effort, as not all individuals are afforded equal prospects to generate income not live in poverty (World Bank, 2005). For instance, less than 15 percent of people born into the bottom half of the education ladder in the median developing country in the 1980s made it to the top quarter (World Bank, 2018), revealing the extent to which a person's socioeconomic status, such as educational attainment or income level, is partly dependent on circumstances at birth, such as their parents' socioeconomic status (Van der Weide et al, 2021). The literature argues that inequality of opportunity—inequality that stems from circumstances beyond one's control, such as place of birth—can hinder human capital accumulation and growth (Marreno and Rodriguez, 2013; Carranza, 2020; Van der Weide et al., 2024). The philosophical stance, supported by scholars like Arneson (1989), Cohen (1989), Roemer (1993, 1998a), and Ramos and Van de Gaer (2012), posits that individuals should only be accountable for factors within their control, and Mahler and Ramos (2019) argue that inequality arising from circumstances is inherently unfair and should be minimized.

Increased socio-economic mobility and equality of opportunities can help address long-term inequality and promote social stability (World Bank, 2018). Numerous studies have found that greater relative mobility and higher equality of opportunity are associated with lower inequality (Corak 2013; Brunori et al., 2013; World Bank, 2018). The well-known Great Gatsby curve, for example, finds that higher economic mobility is associated with lower income inequality (Krueger, 2012; Jantti et al, 2006; Corak 2013; World Bank, 2018; DiPrete, 2020; Durlauf et al., 2022).

With place of birth as one circumstance that people are born into, the extent to which there is an uneven spatial distribution of resources and services can influence mobility and opportunities (Narayan et al, 2013; Connolly, Corak and Haeck, 2019; Brunori et al 2023a). High spatial inequalities are reflected, for example, in lower access to quality education and healthcare in certain municipalities within the same country (World Bank, 2024), shaping opportunities for the next generation and resulting in lower relative mobility[4] (Connolly, Corak and Haeck, 2019; Chetty and Hendren, 2018; World Bank, 2018). Conversely, evidence for the United States and Canada shows that higher mobility at the subnational level is associated with less residential segregation, lower inequality, higher quality public schools, and stronger social networks and

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[4] Relative mobility is understood as the extent to which a person's socioeconomic status is independent of circumstances at birth, such as their parents' socioeconomic status, place of birth, or sex.

family structures (Chetty et al, 2014; Connolly, Corak and Haeck, 2019; Corak, 2013). Recent studies integrate a subnational focus when studying intergenerational mobility. For instance, within-country heterogeneity is analyzed in Buscha et al (2021) for England and Wales, in Alesina et al (2021) for Africa, in Munoz (2021) for Chile, or in Hong and Gruijters, (2024) for China; and by population groups in Asher et al., (2024) for India. These authors find substantial heterogeneity at the subnational level in mobility. For instance, in the case of Chile the relative mobility in education at the commune level varies from 0.54 in Quemchi to 0.97 in San Pedri de Atacama.

The Latin America and the Caribbean region has long been characterized as one of the most unequal regions (Clavijo et al, 2021; Garparini and Cruces, 2021; Brunori, Ferreira and Neidhöfer, 2023). The nature of that inequality matters: more than 44 percent of current income inequality in LAC measured by the Gini coefficient is attributed to inherited factors, ranging from 44 percent in Argentina to 63 percent in Guatemala (Brunori, Ferreira and Neidhöfer, 2023).[5] Within the region, Colombia stands out as the country with highest income inequality (0.546 Gini in 2023), also one of the highest around the world. Four out of five Colombians consider the distribution of income to be unfair or very unfair (data from Latinobarometer 2023). Inequality of opportunity has been estimated at nearly 47 percent of the total inequality measured by the Gini using the Encuesta de Calidad de Vida (ECV) in 2010 (Brunori et al., 2014).[6] Social mobility has also been very low over time, always in the lowest ranges of international comparisons (Angulo et al, 2012) and tends to be higher in regions with higher income levels (Galvis and Meisel, 2014). International comparisons place Colombia as a country with high absolute mobility but very low relative mobility (Van der Weide et al., 2023).

One dimension of inequalities in Colombia is that of territorial disparities. Individuals living in certain areas of the country have lower access to services and to economic opportunities, perpetuating poverty. For example, in Colombia, certain municipalities have over 90 percent of avoidable infant deaths and of 10-year-old children who cannot read and comprehend a simple text (World Bank, 2024). Yet, while there is national-level data on socio-economic mobility, there is little information on the heterogeneity of socio-economic mobility within the territory, and no recent estimates on inequality of opportunity and how place of birth matters.

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[5] Results in Brunori, Ferreira and Neidhöfer (2023) found that when considering the MLD coefficient, the inherited inequality for Latin America ranged from 16 percent in Argentina to 32 percent in Guatemala. In Colombia, inequality of opportunities explains between than 44 and 47 percent of total inequality when using the Gini coefficient and between 16.9 to 18.75 when reporting the MLD. Nevertheless, in this approach estimates for Colombia include a limited list of circumstances where the municipality at birth is not considered.

[6] Ferreira and Melendez, (2012) have found 20 percent of the total inequality measured by the Mean log Deviation (MLD) using the Encuesta de Calidad de Vida (ECV) in 2010 using Ferreira and Gignoux's (2011) approach.

In this paper we explore two main issues: (i) the extent to which place of birth determines inequality of opportunities and (ii) inter-generational socio-economic mobility in Colombia at the subnational level. First, it proposes new estimates of inequality of opportunity, using more up-to-date data and alternative methods, and considering an additional circumstance relevant to the country context, namely exposure to internal armed conflict. Second, we go beyond national-level measures of intergenerational mobility in education, and develop subnational (department-level) estimates, comparable to those available for a large range of countries, thus allowing for international benchmarking of Colombia's departments. The analysis uses data from the ECV (*Encuesta de Calidad de Vida*) 2019 to 2022.

Our results reveal an important role of place of birth in determining opportunities and mobility. A high share of income inequality in Colombia is predetermined by circumstances at birth, with place of birth impacting people's prospects for inter-generational mobility. For example, around 49 percent of per capita household income inequality as measured by the Gini coefficient is explained by parents' educational background, place of birth, sex, and ethnicity. We also find a significantly higher dependance between parents and children's education in places like Nariño, La Guajira and Vichada (with relative mobility estimated at 0.35, 0.36 and 0.37, respectively), compared to 0.61 in places like Bogotá.

This paper contributes to the literature on inequality of opportunities and inter-generational mobility. First, it expands the research that has focused on these themes. For the inequality of opportunity index, we follow the approach used in Brunori, Hufe and Mahler (2023) and applied in Brunori et al (2024), and Atamanov et al (2024). We provide more recent estimates for Colombia, testing for various methodological approaches, and test the inclusion of top income adjustments methodologies to account for the entire distribution. Second, we go beyond national-level estimates on social mobility, in a country that is highly unequal, to zoom in to the subnational level and show the different prospects that people have depending on where they were born. Third, this paper advances the literature by including the additional circumstance of presence of internal armed conflict in the municipality of birth. The evidence for Colombia shows that presence of internal armed conflict is associated with lower access to services, human capital accumulation and perceptions of liberties and freedom (World Bank, 2024; Arjona et al, 2024), which can affect opportunities.

The paper is structured as follows. Section II outlines the data and methods used to construct measures of inequality of opportunity and subnational inter-generational mobility for Colombia, and Section III presents the main findings around both. Section IV includes several robustness checks for variables with missing information, sensitivity of the results to changing certain circumstances, and an initial testing of innovative methods of top incomes. Section V finalizes with key conclusions and insights.

II. Data and Methods

Inequality of Opportunities

Following Roemer (1998) and Van der Gaer (1993), the main model of Inequality of Opportunities (IOp) distinguishes between circumstances and effort when measuring welfare, such as income. The most common structure for measuring inequality of opportunity follows the form of inequality in predicted income, $I(\tilde{y})$, to inequality in observed income, $I(y)$, where the first refers to predicted income by inherited circumstances or absolute IO (Brunori, Ferreira and Salas-Rojo, 2023). In other words, $\tilde{y}$ can be seen as the contrafactual inequality in income due solely to circumstances at birth or as a smoothed per capita income that measures the average level within each "type" or subgroup with similar observable conditions (Brunori, Hufe and Mahler, 2023). Then, the Relative Inequality of Opportunity (IOr) follows:

$$IOr = \frac{I(\tilde{y})}{I(y)}$$

There is a growing literature on measuring inequality of opportunities, and applications for several countries (Bourguignon, 2018; Ferreira and Peragine, 2016; Ramos and Van de Gaer, 2016; Roemer and Trannoy, 2013; Brunori, Ferreira and Neidhöfer, 2023; Brunori, Hufe and Mahler, 2023; Atamanov et al., 2024). In this paper we follow the Ferreira and Gignoux (2011) accounting for direct ex-ante IO (the so-called lower bound) and building upon Ferreira and Melendez's (2012) application for Colombia.[7] The latter used 1997, 2003, 2008, and 2010 surveys and focused on household and labor income to assess the role of municipality size as well as particular regions in driving inequality. They found that circumstances such as parent's education, municipality size, and rural areas determine disadvantages in terms of inequality of opportunities. Additionally, and understanding the limitations of the latest approach, which potentially leads to create a downward bias, we follow Brunori, Hufe and Mahler's (2023) approach by estimating conditional inference regression trees and random forest.

Following Brunori, Hufe and Mahler (2023), and Atamanov et al.'s (2024) application, the conditional inference regression trees (Conditional Trees) approach consists of partitions of the sample into circumstance types, where a regression tree algorithm divides the data into different nodes (each node being a circumstance). Here, the goal is to predict income outside the sample. At each tree branch, the algorithm

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[7] It is known as the parametric approach. It uses OLS to regress income at the individual level on the circumstances, determining a set of coefficients to calculate a predicted income on average due to circumstances, where differences in income that are orthogonal to circumstances at birth are attributed to effort (Ferreira and Gignoux, 2011).

identifies the circumstance split that results in the most significant income difference.[8] On the other hand, the Random Forest approach consists of hundreds of trees, each utilizing a subset of observations and a subset of circumstances at each node, with the ultimate predictions being the average of all the trees (more methodological details in Brunori, Hufe and Mahler, 2023).The regression tree approach adds more variability to the model, dealing with downward biases more efficiently given that it considers nodes by partitioning the data instead of averages for the entire distribution. Additionally, the forest tree methodology tackles difficulties due to potential small changes in the data that might alter the splitting points, it diminishes arbitrary selection of specifications without any functional form selection needed (Brunori, Hufe, and Mahler, 2023; Atamanov et al., 2024).[9] Refer to the version of the regression tree for Colombia in Annex figure A1.

Using more recent data from the ECV (*Encuesta de Calidad de Vida*, pre- and post-COVID-19 2019 and 2022 surveys), we explore how much individuals' incomes depend on circumstances at birth. The selection of these two years allows assessing how structural inequality of opportunity is in the presence of such a strong economic shock. As measures of living standards, we focus on per capita income inequality and labor income inequality for the population between 25 and 85 years old with reported income.

We include the following circumstances in the measurement of an inequality of opportunities index: (i) Education: the maximum educational level of parents reported in the ECV; (ii) Place of birth: the area of birth (rural or urban); the equivalent region of birth (following Ferreira and Melendez, 2014); the size of the population in the municipality of birth divided into four groups; and a variable that measures the presence of internal armed conflict in the municipality of birth; (iii) Ethnicity: indigenous, NARP (*Negro, Afro Colombian, Raizal or Palenquero*), or neither; (iv) Sex: man or woman, excluded from the household income specification given that it is individual and not at the household level; when included, it is not statistically significant as in Ferreira and Melendez (2014).

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[8] This process uses statistical tests to avoid over-fitting. First, the algorithm circumstances that are significantly related to income, with a p-value less than .01 after a Bonferroni adjusting for multiple tests. It then picks the circumstance with the smallest p-value. For this circumstance, it tests all possible ways to split the data to find the one that shows the biggest difference in income between groups. If the circumstance is continuous or ordered, it chooses a splitting point. If it is categorical, it divides the values into two groups. This process continues until no more significant splits are found or the maximum depth is reached (Atamanov et al., 2024).

[9] We follow Brunori, Hufe and Mahaler's (2018) algorithm. They discuss fine-tuning "tree" and "forest" methods to estimate inequality of opportunity. The goal of fine-tuning is to balance downward (underestimation) and upward (overestimation) biases. For trees, fine-tuning involves selecting an α value that determines when tree nodes are split. A less strict α allows more splits, risking overfitting. To prevent this, cross-validation chooses the α value that best predicts out-of-sample results. For forests, fine-tuning selects values for α, the number of predictors considered at each split, and the number of subsamples used to build the trees. Again, a cross-validation process, based on the "out-of-bag" error, finds the combination of values that minimizes out-of-sample prediction error. In both cases, the goal is to find a model that generalizes well to new data, providing more reliable estimates of inequality of opportunity.

We define a municipality under internal armed conflict based on historical data from Fernandez (2010), LeGrand (1988) included in the Municipal Panel dataset of CEDE (see Acevedo, and Olivella, 2014), and the Violent Presence of Armed Actors in Colombia report (ViPAA, see Osorio et al., 2019). We consider two periods taken from those data sources,[10] where we assume that people registered in the Household Survey (the ECV) who were born during that period in their respective municipality, were exposed to the presence of internal armed conflict, and subsequently we treat that as a circumstance.[11] This definition has limitations given that individuals have the value of 1 if the time of birth overlaps with periods of internal armed conflict in a municipality. Robustness checks such as widening the age period of child exposure to internal armed conflict could be explored in future versions.

We report two measures of inequality: the Mean Log Deviation (MLD) to facilitate comparison with previous studies for Colombia, and the Gini coefficient, which is less sensitive to extreme values and helps address underestimation issues (Aaberge et al., 2011; Palmisano et al. 2022; Brunori et al., 2019; Atamanov et al., 2024).

Intergenerational Mobility in Education

We build upon the International IGM database constructed by Van der Weide et al. (2024). To ensure methodological consistency, we initially use the Colombia ECV 2013 survey to replicate results for the reference year in the International IGM database. However, this paper draws from more recent data. Specifically, we pool the ECV 2019, 2021, and 2022 to strengthen sample power to be able to disaggregate results at the department level and include department of birth in the analysis.[12] Colombia has 32 departments and 1,112 municipalities.

We concentrate on two common concepts in the inter-generational mobility literature: absolute and relative mobility. Absolute mobility refers to the proportion of individuals who achieve a higher level of education than their parents. Relative mobility, on the other hand, indicates the extent to which an individual's socioeconomic success is not influenced by the socioeconomic status of their parents. There are several ways to measure inter-generational mobility. Selecting similar indicators to those in the international

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[10]The first period encompasses the years 1901-1931 and 1948-1953, during which the presence of partisan insurgency by municipality is documented. The second period begins in 1973, with annual data available, and considers attacks by various violent actors, including guerrillas, paramilitaries, and military forces. We estimate the presence of violence in a municipality within a five-year span for any actor. Consequently, we imputed a dummy variable (internal armed conflict presence) to the ECV by municipality and year of birth, assigning a value of 1 when the individual was born in that particular municipality during the specified period.

[11] Due to the absence of data for the periods 1932-1947 and 1954-1973, we assume the presence of internal armed conflict only in municipalities where conflict was persistent. This means we consider municipalities that reported conflict presence both before and after these periods. We then imputed this information to household members in the ECV based on their place of birth and year of birth.

[12] See annex Figure A9 comparing sample sizes.

database allows to draw comparisons across countries, to assess how Colombia's departments fare in educational mobility compared to countries of different income levels. Among a set of indices estimated in Van der Weide et al (2024) we focus on two. First, the share of respondents with more years of schooling (y_{child}) than both of their parent's (y_{parent}) conditional on parents not reaching the maximum years of schooling as a measurement of absolute mobility:

$$IMG_a = P\big(y_{child} > y_{parent} \,|y_{parent} < \max in\ sample\big)$$

Second, 1-beta, or 1 minus the coefficient from regressing respondent's years of schooling on parent's years of schooling as a measurement of relative mobility:

$$IMG_r = 1 - \beta,$$

$$\beta\ from\ y_{child} = \alpha + \beta * y_{parent} + e$$

There is a debate regarding potential bias when using the regression coefficient relative to a correlation coefficient. For instance, Emran et al. (2019) use data from Bangladesh and India to estimate IMG from coresident samples (a sample which is only available for individuals living in the same household with their parents) showing significant downward bias in the regression coefficient, while the correlation coefficient is estimated to have a much smaller bias. Nevertheless, Munoz and Siravegna (2023) show that the correlation coefficient is not always less biased by co-residency compared to the regression coefficient. Moreover, in terms of relative mobility, the Pearson correlation coefficient and rank-based indicators derived from education data appear less reliable for ranking economies compared to the intergenerational regression coefficient, despite having a smaller co-residence bias. Given the findings in the latest study, we report the 1-beta coefficient as a measure of relative IMG. Nevertheless, when computing the correlation coefficient, we found a correlation between both indicators of about 0.81.

However, it is important to raise a challenge when dealing with education variables, which is commonly observed in coarse bins. The literature identifies challenges in measuring IMG due to unobservable parent-child correlations within broad education categories, making conventional rank mobility measures potentially biased (Asher et al., 2017). In other words, parent-child correlations within bins may be unobservable. Parents with the same educational level may have different true outcomes due to education quality or broad survey categories, leading to different expected performances for their children (Van de Weide et al., 2023). Certain authors (Asher et al. 2017, 2024) have tried to tackle this issue by developing a nonparametric method to bound mobility measures and propose a new measure of upward mobility,

considering the expected education rank of a child born to parents in the bottom half of the education distribution.

III. Results

Inequality of Opportunity

Table 1 shows that approximately one-fifth of income inequality using MLD can be attributed to circumstances at birth, but about a half when considering the Gini coefficient.[13] For labor income, this rises, and ranges between 22.4 to close to 30 percent in MLD, and between 48.6 and 50.5 percent using the Gini coefficient.[14]

Table 1. Results on absolute and relative IO, 2022

	Panel A: MLD					
	Outcome: Per capita Income			Outcome: Labor Income		
	Parametric	Conditional Trees	Random Forest	Parametric	Conditional Trees	Random Forest
IO	0.131	0.121	0.124	0.122	0.104	0.112
IOr	23.6	21.1	21.7	29.6	22.4	23.9
Obs	151,882	151,882	151,882	90,996	90,997	90,997
	Panel B: Gini					
	Outcome: Per capita Income			Outcome: Labor Income		
	Parametric	Conditional Trees	Random Forest	Parametric	Conditional Trees	Random Forest
IO	NA	0.274	0.278	NA	0.255	0.265
IOr	NA	48.5	49.2	NA	48.6	50.5
Obs	NA	151,882	151,882	NA	90,997	90,997

Next, we aim at determining to what extent each circumstance explains the inequality of opportunity both in per capita income and labor income. Table 2 presents the Shapley value of circumstances under the parametric approach and the contribution of each circumstance estimated under the Random Forest

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[13] The specification reported in Table 1 includes variables such as ethnicity, parent's education with imputations for unreported registers using one variable for both parents (specification 1 in table 4, see robustness checks section), as well as a pool of place at birth variables (born rural/urban area, born municipality size, presence of internal armed conflict in born municipality).
[14] This is similar to the results we found for 2019 (presented in Table A1), although the Inequality of Opportunity index (IOr) is slightly higher for total household per capita income in 2022 compared to 2019.

methodology.[15] Our findings suggest the place of birth, all together, accounts for around a third of the total inequality of opportunity (circumstances) but could explain nearly 53.6 percent when using the Random Forest methodology. The latter suggests that under the parametric approach some crucial variables in the Colombian context such as the department of birth could be underestimated.[16]

Table 2. Shapley value and Contribution circumstances for the main specification

	Shapley (under parametric approach using MLD) %		Contribution (under random forest) %	
	Per capita Income	Labor Income	Per capita Income	Labor Income
Parents Education	**54.7**	**53.6**	**41.2**	**41.6**
Ethnicity	**6.5**	**9.2**	**5.2**	**6.4**
Place of birth	**38.8**	**35.7**	**53.6**	**50.1**
Department of birth	2.7	2	22.5	23.6
Municipality category of birth	17.4	17.1	12.1	8.8
Rural/Urban Municipality	10.3	11	9.2	9.2
Presence of Internal Armed Conflict in Municipality when Born	8.4	5.6	9.8	8.5
Sex	**na**	**1.6**	**na**	**1.9**

Intergenerational education mobility

With around half of the inequality of opportunity determined by individuals' socio-economic background (namely parents education), we then explore inter-generational mobility in education, bringing in the spatial lens to opportunities within Colombia.

First, the International IGM database reveals that, as in LAC countries, Colombia faces high absolute levels of mobility. Seventy-eight percent of Colombian adults have more years of schooling that both of their parents. Nevertheless, relative mobility is among the lowest worldwide, well below that of OECD countries and of some countries in the region such as Brazil or Argentina. That is, there is high persistence in the ranking of the education distribution across generations. In fact, Colombia is one of the few countries in

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[15] In annex table A4 we report the Shapley value for different specification considering the parametric approach.

[16] One potential reason for these differences is that the parametric approach enforces a fixed functional form on the relationship between circumstances and income. For instance, the impact of parental education might differ by birth region, but the method assumes it is uniform for all, leading to a downward bias in IOp, and specifically in variables with higher variation and more categories such as the department of birth with 33 categories. In contrast and as explained in Brunori, Ferreira and Neidhöfer (2023), the Random Forest approach addresses both downward and upward biases efficiently by interacting all circumstance variables in the regression, assigning individuals to the average income within their specific type and under collections of hundreds of trees using a subsample of observations and circumstances at each node and tree.

the world (among those with available data) where high absolute mobility coexists with extremely low levels of relative mobility (Figure A1).

One of the main contributions of this paper, as mentioned, is to explore mobility outcomes at the subnational level. We find that there is high heterogeneity of social mobility in education across Colombian departments. Figures 1 and 2 and Table 4 present mobility indices, absolute and relative, for Colombia's departments and separately for sons and daughters.

In terms of absolute mobility, Colombian departments display high mobility, showing the country's overall progress in educational attainment (Figure 1). However, there is high dispersion in relative mobility, revealing wide spatial disparities in the opportunities to move up the socio-economic ladder (Figure 2). In general, peripheric departments in the Pacific, Caribbean and Orinoquía Region show the lowest rates of absolute mobility (Figure A2). Some of them also experience low levels of relative mobility (Figure A3). While Cundinamarca and Casanare have the highest levels of both absolute and relative mobility, La Guajira, Guainía and Vichada are among the departments with the lowest mobility in the country. Women are more likely to surpass the education of their parents, but in some departments such as Guainía or Amazonas the gender gap in relative mobility is considerably large (Table A3). Compared to OECD countries, with an average relative mobility in education of 0.67, certain departments display even lower levels than the already-low mobility exhibited by the Colombia national figure (Table 3). See Annex Table A2 for more granular comparisons with OECD countries.

Figure 1. Absolute Mobility: Years of education (share of adults, YOS), cohort 1980

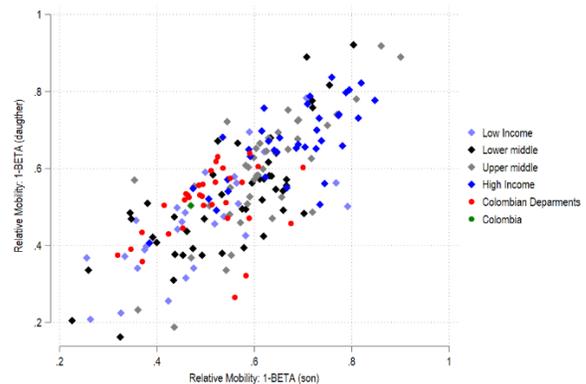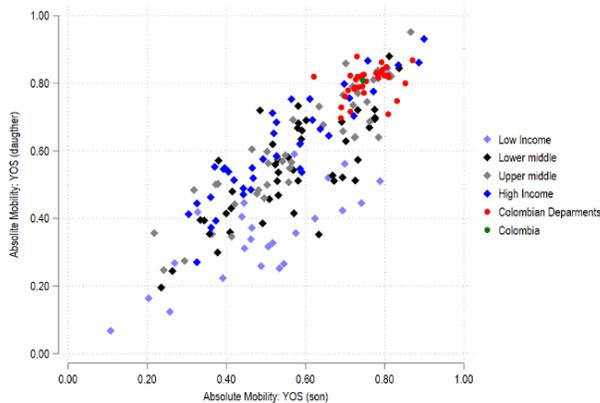**Figure 2. Relative Mobility: 1-Beta Coefficient, cohort 1980**

Table 3. Intergenerational mobility, all children, and maximum years of education for both parents, cohort 1980

Department	Observations in HS	Parents education (mean)	Children education (mean)	Absolute Mobility	Relative Mobility
OECD	56665	12.3	14	0.57	0.67
San Andres	840	9.7	13	0.72	0.67
Bogotá	3918	9.2	13.5	0.77	0.61
Middle East & North Africa	60687	5.5	9.5	0.66	0.61
Atlántico	3913	8	11.7	0.73	0.6
East Asia & Pacific	38925	7.3	9.6	0.6	0.6
Cundinamarca	2809	5.8	10.9	0.81	0.58
Arauca	2077	4.9	9.1	0.76	0.57
Casanare	1744	4.8	9.9	0.82	0.57
Amazonas	1814	4.7	9.4	0.79	0.57
Chocó	2478	5.3	9.5	0.71	0.57
Europe & Central Asia	10746	11.2	12.2	0.48	0.57
Quindío	1859	7.1	11.7	0.77	0.57
Latin America & Caribbean	53459	6.3	9.5	0.68	0.56
Valle del Cauca	3539	7.5	11.6	0.75	0.56
Cesar	2899	5.5	10.4	0.78	0.54
Risaralda	2380	6.4	11	0.78	0.53
Guaviare	892	4.5	9.5	0.82	0.53
Meta	2637	6.3	11	0.79	0.52
Sucre	3158	4.7	9.9	0.81	0.52
Magdalena	3044	5.7	9.9	0.76	0.51
Bolivar	4101	6.1	10.1	0.75	0.51
Córdoba	3431	4.8	9.8	0.81	0.51
Antioquia	4380	6.7	11.1	0.77	0.5
Tolima	3031	6	10.7	0.79	0.5
Norte de Santander	3338	5.8	10.3	0.76	0.5
Caldas	2666	6.4	11.3	0.8	0.5
Colombia	89282	6.5	11	0.78	0.49
Santander	3464	6.6	11.4	0.8	0.49
Caquetá	2537	4.8	9	0.78	0.49
South Asia	43300	4.3	7.4	0.55	0.48
Putumayo	1762	4.7	9.4	0.82	0.46
Boyacá	3399	5.6	10.8	0.83	0.45
Vaupes	1534	3.2	8.1	0.87	0.45
Huila	2966	5.3	10.2	0.83	0.43
Guainía	1622	3.5	7.4	0.76	0.41
Cauca	3317	4.4	9	0.81	0.4
Vichada	1542	4.1	7.2	0.69	0.37
La Guajira	2818	4.7	8.8	0.71	0.36
Nariño	3373	4.8	9.2	0.81	0.35

In terms of trends, absolute mobility had been increasing until the 1980s cohort, with a higher pace in places that are considerably poor such as Amazonas, Oriental and even the Caribbean region (Figure 3). This is likely explained by a ceiling effect: as economies grow and the average level of education rises, it becomes increasingly challenging for individuals to surpass the achievements of their parents (Narayan et al., 2018). In terms of relative mobility, it has been increasing over time and the gap between regions has shrunk along cohorts (Figure 4). Nevertheless, there are still differences in opportunities between regions (Figures 3 and 4), with poorer areas experiencing lower mobility (Figures A4 to A7).

Figure 3. Trends in Absolute Mobility by cohorts grouped by regions
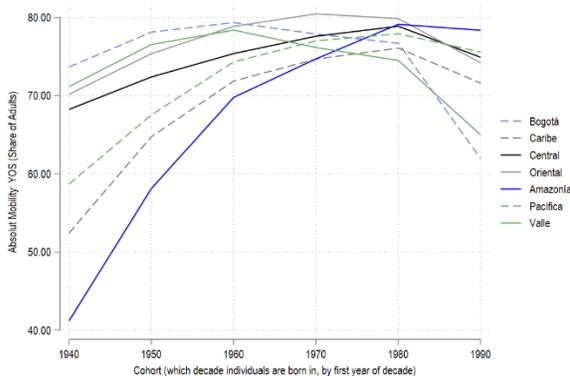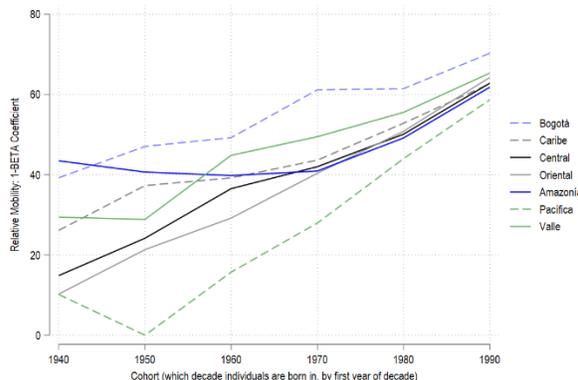
Figure 4. Trends in Relative Mobility by cohorts grouped by regions

Lower educational mobility is associated with poverty and overall inequality. Departments with high poverty (monetary and multidimensional) and inequality levels also have low absolute mobility (Figure A8) and low relative mobility (Figure A9 and Figure A10). For instance, La Guajira, Vaupés, and Guainía have relatively lower levels of both absolute and relative mobility as well as high multidimensional poverty levels, similar to that of the south-west region (Cauca, Narino, Putumayo, and Caquetá).

IV. Robustness Checks

Several robustness checks are carried out and included in Tables 4 and A1 to A4 to assess the sensibility of the index to one of the main variables included, namely that of education of the parents. The main challenge with these variables stems from choices of including mother or father's education separately or maximum education (one variable for both parents), and for filling missing values in the dataset (more so for mothers' education). Retrospective variable (education of parents) tends to suffer from non-response. In particular,

given instances of missing data on parents' education (mother and/or father), we test imputation techniques for missing parent education.

We run multiple specifications for consistency checks under different assumptions treating the variable education of parents. First, we impute the education level for missing observations in the retrospective variable, given that the Household Survey separately asks for individual education within the household. We compute estimates by considering the maximum education level of both parents, rather than using two separate variables (one for the mother and one for the father). In cases in which some children do not report their parents' education, we identify the actual level self-reported by the individual by considering their relationship.[17] In the second specification type, we do not perform any imputation but consider the maximum educational level of both parents. In contrast, in the third and fourth specifications, we treat the parents' education variables separately for each parent. Specifically, we impute missing values in the third specification but do not perform imputation in the fourth specification.

The IOr decreases in specifications that include imputed values and larger sample sizes. For example, the IOr in specifications 1 and 3, when considering imputed values, are approximately 1 percentage point lower than when no imputation is applied to parental education. This is particularly notable with the IOr standing at 45 percent when a single variable for both parents is used (specification 1), and 46.3 percent when the education levels of the mother and father are computed separately (specification 3). On the other hand, when the sample size is reduced (specifications 3 and 4, see Table 4 below) due to the separate consideration of mother's and father's education, the Inequality of Opportunities (IOr) increases slightly. Specifically, the IOr rises from 48.5 percent in specification 1 to 49.1 percent in specification 3, and from 48.8 percent in specification 2 to 49.5 percent in specification 4.[18]

Second, we conduct multiple specifications for consistency checks by incorporating additional variables that more accurately capture the place of birth. We consider specifications both with and without the population size of the birth municipality, defined as follows: i) fewer than 50,000 inhabitants; ii) more than 50,000 but less than 100,000 inhabitants; iii) more than 100,000 but less than 500,000 inhabitants; and iv) more than 500,000 inhabitants. Excluding municipality variables, as well as not accounting for critical circumstances such as the presence of conflict in Colombia in the municipality of birth, could lead to an underestimation of the role of birth circumstances in explaining inequality of opportunities. For instance, in Specification 1, the IOr increases by 1.7 percentage points (pp) when including variables for the

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[17] For example, a grandmother to a mother living in a household where the household head is her child, but the mother has not reported information in the self-reported variable.
[18] Annex tables A1 and A2 present results using the parametric approach.

municipality of birth, and by an additional 1.8 pp when considering the dummy variable for the presence of internal armed conflict in the birth municipality.

Table 4. Results on absolute and relative IO for different specifications using Conditional Trees, (Gini reported for 2022)

Specification type/key variable		Per capita income			Labor income		
		Without municipality variables	With municipality variables	Municipality + internal armed conflict	Without municipality variables	With municipality variables	Municipality + internal armed conflict
S1: Education imputed, one variable for both parents	IO	0.255	0.264	0.274	0.247	0.255	0.255
	IOr	45.0%	46.7%	48.5%	47.2%	48.7%	48.6%
	N		151,883			90,997	
S2: Education no imputed, one variable for both parents	IO	0.264	0.271	0.278	0.264	0.268	0.269
	IOr	46.2%	47.5%	48.8%	49.9%	50.7%	51.0%
	N		138,262			82,917	
S3: Education imputed, father and mother separated	IO	0.265	0.274	0.281	0.253	0.270	0.270
	IOr	46.3%	47.8%	49.1%	47.7%	50.9%	51.0%
	N		124,676			75,098	
S4: Education no imputed, father and mother separated	IO	0.270	0.281	0.287	0.271	0.281	0.126
	IOr	46.6%	48.5%	49.5%	50.3%	52.2%	52.3%
	N		111,812			66,796	

Finally, given that the literature has identified that household surveys often overlook high-income households, (Alvaredo et al. 2013, Atkinson et al. 2011, Bourguignon, 2018, Burkhauser et al. 2012, Cowell and Flachaire, 2007, Jenkins 2017, Lustig, 2020; Cowell and Flachaire, 2007; Morgan 2018), and it is especially true for Colombia (Alvaredo and Londono, 2013; Diaz, 2015), we implement an additional exploratory analysis to measure the IO in Colombia accounting for top incomes. High-income earners represent a small population share and tend to underreport or even not respond about their income or consumption in household surveys (Alvaredo and Londono, 2013; Diaz, 2015; Anand and Segal, 2016). For example, numerous studies have shown that in low- and middle-income countries, per capita income or consumption measured by household surveys frequently lags behind welfare outcomes from National Accounts (Altimir, 1987; Fesseau and Mantonetti, 2013; Alvaredo et al, 2018).

In that regard, several methodologies are developed to correct inequality indicators by taking into account the missing top income households (Bourguignon, 2018; Lustig, 2020; Cowell and Flachaire, 2015). As part of the robustness checks, we applied the methodology proposed by Blanchet et al. (2022), which uses

together replacing and reweighting approaches to adjust the top of the income distribution with an endogenous selection of the merging point. One of the advantages of the methodology relies on the potential scope of replicating socioeconomic characteristics within the household, which allows us to get data on education for the corrected population by assuming the socioeconomic characteristics of the replaced population within the survey.

Table 5. Results on absolute and relative IO for different specifications adjusting for the missing rich, 2022.

Specification type/key variable		Per capita income		
		Without municipality variables (1)	With municipality variables (2)	Municipality + internal armed conflict (3)
S1: Education imputed, one variable for both parents	IO	0.382	0.430	0.420
	IOr	64.2%	72.2%	70.5%
	N		152,609	
S2: Education no imputed, one variable for both parents	IO	0.417	0.459	0.466
	IOr	69.2%	76.3%	77.3%
	N		138,963	
S4: Education imputed, father and mother separate	IO	0.416	0.431	0.434
	IOr	68.6%	71.0%	71.6%
	N		125,345	
S3: Education no imputed, father and mother separate	IO	0.420	0.446	0.448
	IOr	68.6%	72.9%	73.2%
	N		112,389	

We followed a similar approach and application in Baquero et al (2023) for Colombia using tax records, but this time adjusting the ECV for 2022 to better capture the entire income distribution, and then estimate IO indicators as in the table 5. Our estimates suggest an increase in the Gini coefficient from 0.565 without adjustment to 0.595 by correcting for the missing rich. The adjustment supposes a significant increase in the inequality of opportunities in absolute terms for specifications 2 and 3, as well as an increase in the relative inequality of opportunities index driven by the increment in the absolute IO,[19] given the adjustment at the top of the income distribution. IOr is estimated around 70.5 percent, which is close to the inherited inequality found in South Africa, ranging from 67.4 to 73.6 percent (see Brunori, Ferreira and Salas-Rojo, 2023).

Nevertheless, the literature has identified the need to validate methodologies that adjust for the top earners by comparing multiple techniques (Lustig, 2020). This is an area that warrants further exploration. Additionally, future research in this domain can focus on two main areas: i) improving the identification of socioeconomic characteristics of top earners through imputation techniques, and ii) using linked data with

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[19] Results using the parametric approach are shown in Annex table A3, where despite a slight increase in the absolute IOp, the relative IO decreases.

administrative records to better capture the actual socioeconomic characteristics of households along the entire distribution. In this context, Colombia, as a data-rich country, possesses a set of administrative records, such as the Registro Social de Hogares, which can potentially be explored as studies by Leites et al (2022) in Uruguay.

V. Conclusions

This paper presents new estimates of inequality of opportunity in Colombia and subnational (department-level) estimates of intergenerational mobility in education. On the latter, absolute mobility is measured as the share of respondents with more years of schooling than both of their parent's, and relative mobility as 1 minus the coefficient from regressing the respondent's years of schooling on parent's years of schooling.

We find a large role for place of birth in shaping inequality of opportunity, and significant heterogeneity in inter-generational education mobility at the subnational level. The results show that around half of inequality of total and labor income is explained by individuals' circumstances at birth and that, among those, 53.6 and 50.1 percent, respectively, are attributed to place of birth. We also find that educational mobility varies significantly at the subnational level, with people who are born in poorer places facing lower relative mobility. Bogotá, for one, has the highest relative mobility in education and closer to that of the OECD average, while poorer departments such as Nariño, La Guajira and Vichada have very low relative mobility.

The estimates presented in this paper shed light on the vast spatial disparities that can take place in one country and that are masked by national estimates. They offer an opportunity to bring these inequalities to the forefront of the debate and can have implications for the country's poverty and inequality reduction agendas, including on policies to ensure equity in access to opportunities and promote territorial development.

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Annex

Table A1. Results on absolute and relative IO for different specifications using a parametric approach (MLD reported), 2019

Specification type/key variable		Capita income			Labor income		
		Without municipality	With municipality	Municipality + internal armed conflict	Without municipality	With municipality	Municipality + internal armed conflict
S1: Education imputed, one variable for both parents	IO	0.103	0.118	0.133	0.101	0.121	0.136
	IOR	16.5%	19.0%	21.4%	21.9%	26.2%	29.5%
	N			167,033		101,361	
S2: Education no imputed, one variable for both parents	IO	0.108	0.124	0.137	0.116	0.137	0.153
	IOR	17.1%	19.6%	21.7%	24.2%	28.5%	31.9%
	N			149,986		91,167	
S4: Education imputed, father and mother separately	IO	0.115	0.131	0.151	0.122	0.141	0.160
	IOR	18.0%	20.4%	23.4%	24.9%	28.8%	32.6%
	N			130,753		79,880	
S3: Education no imputed, father and mother separately	IO	0.124	0.142	0.156	0.140	0.162	0.179
	IOR	18.8%	21.6%	23.6%	27.7%	32.2%	35.4%
	N			117,801		71,484	

Table A2. Results on absolute and relative IO for different specifications using a parametric approach (MLD reported), 2022

Specification type/key variable		Per capita income			Labor income		
		Without municipality variables (1)	With municipality variables (2)	Municipality + internal armed conflict (3)	Without municipality variables (4)	With municipality variables (5)	Municipality + internal armed conflict (6)
S1: Education imputed, one variable for both parents	IO	0.095	0.111	0.131	0.091	0.107	0.122
	IOr	17.1%	20.0%	23.6%	22.3%	26.1%	29.6%
	N			151,882			90,996
S2: Education no imputed, one variable for both parents	IO	0.106	0.122	0.135	0.107	0.123	0.133
	IOr	18.6%	21.5%	23.8%	25.2%	29.1%	31.3%
	N			138,262			82,916
S3: Education imputed, father and mother separated	IO	0.113	0.128	0.144	0.112	0.127	0.139
	IOr	19.7%	22.2%	25.1%	26.0%	29.6%	32.3%
	N			124,675			75,097
S4: Education no imputed, father and mother separated	IO	0.123	0.140	0.157	0.131	0.162	0.157
	IOr	20.9%	23.7%	26.6%	29.2%	33.3%	35.0%
	N			111,812			66,795

Table A3. Results on absolute and relative IO for different specifications adjusting for the missing rich using a parametric approach (MLD reported), 2022

Specification type/key variable		Per capita income		
		Without municipality variables (1)	With municipality variables (2)	Municipality + internal armed conflict (3)
S1: Education imputed, one variable for both parents	IO	0.081	0.108	0.128
	IOr	13.0%	17.2%	20.4%
	N		152,608	
S2: Education no imputed, one variable for both parents	IO	0.092	0.120	0.138
	IOr	14.4%	18.7%	21.5%
	N		138,963	
S4: Education imputed, father and mother separate	IO	0.101	0.128	0.149
	IOr	15.5%	19.6%	22.7%
	N		125,345	
S3: Education no imputed, father and mother separate	IO	0.111	0.141	0.155
	IOr	16.6%	21.0%	23.1%
	N		112,389	

Table A4. Shapley value of circumstances: Including variables regarding the place of birth at municipality level

	Per capita income			Labor Income		
	Without municipality (1)	With municipality (2)	Municipality + internal armed conflict (3)	Without municipality (4)	With municipality (5)	Municipality + internal armed conflict (6)
Parents Education	83.6	57.2	**54.7**	81.5	55.8	**53.6**
Ethnicity	12.6	10.3	**6.5**	13.1	10.5	**9.2**
Born Department	3.8	1.8	**2.7**	3.9	1.9	**2.0**
Born Municipality Group	na	19.3	**17.4**	na	17.7	**17.1**
Rural/Urban Municipality	na	11.3	**10.3**	na	12.2	**11.0**
Presence of Internal Armed Conflict in Municipality of birth	na	na	**8.4**	na	na	**5.6**
Sex	na	na	**na**	1.5	2.00	**1.6**

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Table A5. Results on absolute and relative intergenerational mobility, OECD and Colombian departments

Country/Department	Observations in HS	Parents education (mean)	Children education (mean)	Absolute Mobility	Relative Mobility
United Kingdom	761	12.79	15.15	0.65	0.82
Korea, Rep.	2042	11.69	14.98	0.77	0.81
New Zealand	116	14.33	14.97	0.52	0.81
Israel	1486	12.47	13.65	0.47	0.80
Denmark	519	13.83	14.39	0.56	0.80
Australia	2843	13.38	13.62	0.38	0.77
Iceland	248	14.85	16.40	0.60	0.76
Finland	1025	13.86	15.24	0.58	0.76
Netherlands	727	12.65	15.51	0.71	0.75
Canada	3305	14.41	14.71	0.41	0.74
France	804	11.84	14.88	0.73	0.73
Germany	1346	14.71	15.06	0.46	0.73
Japan	380	13.76	14.31	0.37	0.71
Lithuania	796	13.82	14.56	0.47	0.70
Belgium	870	12.39	14.75	0.66	0.69
Greece	218	10.64	13.37	0.66	0.68
Spain	1028	9.03	15.49	0.87	0.68
Norway	809	14.25	14.87	0.51	0.67
United States	3660	14.12	14.41	0.36	0.67
San Andres	840	9.65	12.98	0.72	0.67
Italy	332	11.80	13.66	0.50	0.67
OECD	145947	12.15	13.94	0.58	0.67
Switzerland	774	13.66	12.34	0.30	0.66
Poland	1143	11.46	14.43	0.75	0.65
Ireland	1459	11.05	15.82	0.92	0.65
Sweden	769	14.05	14.55	0.47	0.64
Costa Rica	1681	6.82	9.00	0.57	0.64
Slovenia	689	12.53	14.18	0.61	0.64
Chile	12708	10.47	13.01	0.65	0.62
Bogotá	3918	9.19	13.49	0.77	0.61
Estonia	1062	14.58	14.47	0.38	0.61
Latvia	284	13.80	13.96	0.46	0.61
Slovak Republic	461	12.79	13.89	0.56	0.61
Czechia	1291	13.53	13.97	0.47	0.61
Atlántico	3913	8.00	11.71	0.73	0.60
Mexico	7928	7.85	10.98	0.68	0.60
Cundinamarca	2809	5.84	10.85	0.81	0.58
Arauca	2077	4.88	9.08	0.76	0.57
Casanare	1744	4.78	9.92	0.82	0.57
Amazonas	1814	4.74	9.38	0.79	0.57
Chocó	2478	5.29	9.52	0.71	0.57
Quindío	1859	7.14	11.69	0.77	0.57
Valle del Cauca	3539	7.46	11.57	0.75	0.56
Cesar	2899	5.49	10.37	0.78	0.54
Risaralda	2380	6.35	11.01	0.78	0.53
Guaviare	892	4.49	9.46	0.82	0.53
Meta	2637	6.27	11.02	0.79	0.52
Sucre	3158	4.74	9.89	0.81	0.52
Austria	955	12.94	14.37	0.57	0.52

Portugal	726	8.08	12.39	0.81	0.52
Magdalena	3044	5.66	9.91	0.76	0.51
Bolivar	4101	6.10	10.10	0.75	0.51
Córdoba	3431	4.81	9.84	0.81	0.51
Antioquia	4380	6.68	11.10	0.77	0.50
Tolima	3031	6.04	10.67	0.79	0.50
Norte de Santander	3338	5.85	10.25	0.76	0.50
Caldas	2666	6.37	11.31	0.80	0.50
Colombia	89282	6.53	11.01	0.78	0.49
Santander	3464	6.58	11.39	0.80	0.49
Caquetá	2537	4.79	9.00	0.78	0.49
Putumayo	1762	4.66	9.35	0.82	0.46
Boyacá	3399	5.62	10.80	0.83	0.45
Vaupes	1534	3.18	8.13	0.87	0.45
Huila	2966	5.28	10.22	0.83	0.43
Türkiye	735	6.44	10.31	0.70	0.42
Guainía	1622	3.48	7.40	0.76	0.41
Cauca	3317	4.42	9.04	0.81	0.40
Hungary	685	12.22	13.15	0.46	0.40
Vichada	1542	4.06	7.20	0.69	0.37
La Guajira	2818	4.74	8.76	0.71	0.36
Nariño	3373	4.78	9.24	0.81	0.35

Table A6. Results on absolute and relative intergenerational mobility by gender in Colombian departments

Department	Absolute mobility (years of education)		Relative mobility (1-beta)	
	Girls	Boys	Girls	Boys
Bogotá	0.79	0.74	0.64	0.59
Arauca	0.77	0.75	0.63	0.52
Cundinamarca	0.88	0.73	0.62	0.52
Atlántico	0.76	0.7	0.61	0.61
Casanare	0.84	0.8	0.6	0.54
San Andres	0.82	0.62	0.6	0.7
Valle del Cauca	0.78	0.71	0.59	0.51
Quindío	0.81	0.73	0.57	0.55
Cesar	0.82	0.74	0.56	0.52
Chocó	0.73	0.69	0.56	0.57
Risaralda	0.81	0.75	0.56	0.49
Sucre	0.83	0.79	0.56	0.49
Bolivar	0.78	0.72	0.53	0.49
Caldas	0.82	0.78	0.53	0.46
Magdalena	0.79	0.72	0.53	0.49
Norte de Santander	0.79	0.73	0.53	0.46
Tolima	0.82	0.74	0.53	0.47
Santander	0.83	0.78	0.52	0.46
Córdoba	0.82	0.8	0.51	0.51
Meta	0.83	0.75	0.51	0.54
Antioquia	0.82	0.71	0.5	0.5
Putumayo	0.82	0.81	0.5	0.41
Caquetá	0.82	0.73	0.47	0.54
Guaviare	0.8	0.85	0.47	0.59
Amazonas	0.75	0.83	0.46	0.68
Boyacá	0.85	0.8	0.45	0.45
Cauca	0.82	0.81	0.43	0.37
Huila	0.86	0.79	0.43	0.42
Vichada	0.7	0.69	0.39	0.35
Nariño	0.82	0.8	0.37	0.32
La Guajira	0.72	0.71	0.36	0.37
Vaupes	0.87	0.87	0.32	0.58
Guainía	0.71	0.81	0.27	0.56

Figure A1. Regression Tree for Colombia

Figure A2. Absolute and Relative mobility around the world, cohort 1980.

Figure A3. Absolute Mobility: Years of education (share of adults, YOS), cohort 1980

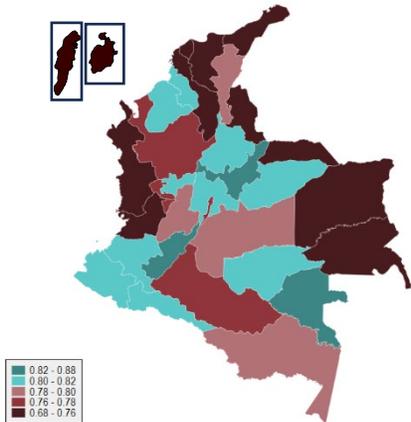**Figure A3. Relative Mobility: 1-Beta Coefficient, cohort 1980**

0.82 - 0.88
0.80 - 0.82
0.78 - 0.80
0.76 - 0.78
0.68 - 0.76

.5821 - .6793
.5321 - .5821
.508 - .5321
.4597 - .508
.3384 - .4597

Figure A4. Absolute Mobility by cohorts grouped by department's poverty levels.

Figure A5. Relative Mobility by cohorts grouped by department's poverty levels.

Figure A5. Absolute Mobility by cohorts grouped by gender and poverty status

Figure A7. Relative Mobility by cohorts grouped by gender and poverty status

Figure A6. Relationship between absolute mobility and welfare indicators

Panel A: Absolute Mobility vs Multidimensional Poverty

Panel B: Absolute Mobility vs Income Inequality (Gini coefficient)

Panel C: Absolute Mobility vs Monetary Poverty (%)

Figure A7. Relationship between relative mobility and welfare indicators
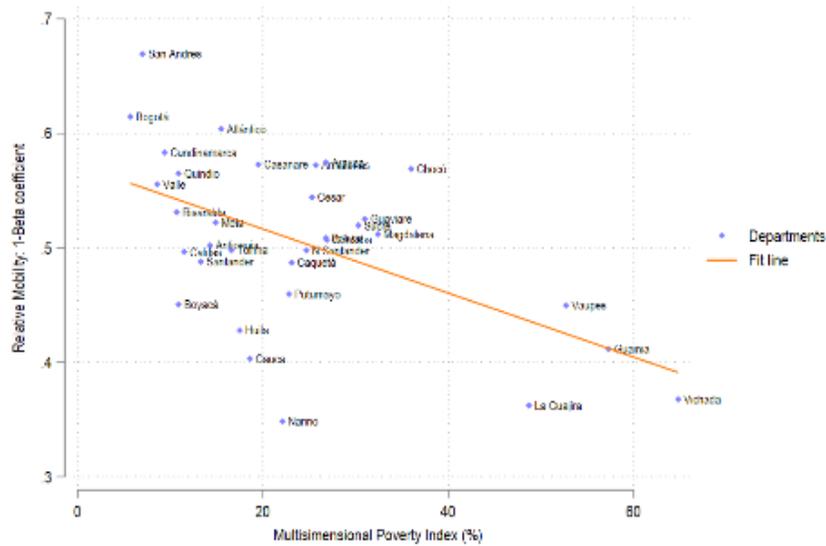
Panel A: Relative Mobility vs Multidimensional Poverty

Panel B: Relative Mobility vs Income Inequality

Panel C: Relative Mobility vs Monetary Poverty
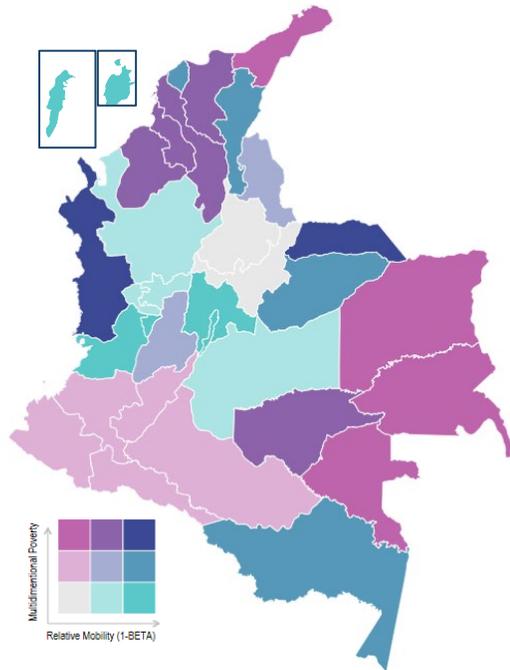
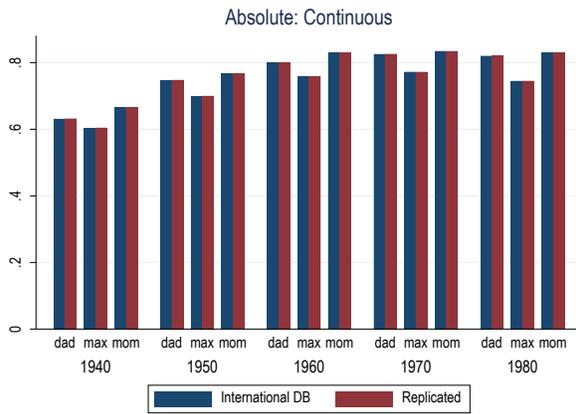**Figure A8. Multidimensional vs Relative Mobility, cohort 1980**

Figure A9. Replicating overall absolute and relative indicators for ECV 2013,

Panel A: Absolute Mobility

Panel B: Relative Mobility