Intergenerational Structural Change in 40 years
The Role of Occupational Changes for Income Growth, Inequality, and Social Vulnerability in Brazil

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Aim

This paper analyzes the role of structural change on Social Welfare and Development for two fathers and sons generations: from 1972-81 to 1996 and from 1990-99 to 2014

Estimating fathers' income

To implement the TSIV, it was used the National Household Sample Surveys of 2014 and 1995, and the editions from 1996 and 1976. The first and third ones, referred as "sons' sample", give information about their income, as well as the parent's characteristics of educational levels and occupation reported by the sons. In the other hand, the 1995 and 1976's sample, or the "parents' samples" give data about the father's incomes and characteristics in a synthetic way. I restrict the sample to workers from 30 to 39 years old, so there is two mobility processes, from 1972-81 to 1996 and 1990-99 to 2014. There's 9 dummies for each occupational category, besides 9 educational levels. For 1996 and 2014, I used 1976 and 1995 PNAD for estimating schooling and occupational status returns, following Bjorklund andJantti (1997) and Pero and Szerman (2008). The specification for 1996 or 2014 follows as showed, below.

$$Y_{i1976/1995} = \gamma_0 + \gamma_1 \times S_i + \gamma_2 \times Ocup_i + \gamma_3 \times Black_i + \gamma_4 \times Age + \gamma_5 \times Age^2 + \varepsilon_i \quad (5)$$

Where $Y_{i1977/1995}$ is vector of the observed log of labor income of all men that have children born from 1957 to 1966 (for the 1976 sample) or from 1975 to 1984 (for the 1995 sample). S_i is their schooling level, $Ocup_i$ is a matrix of dummies for their occupational category and $Black_i$ is a dummy for their race. Finally, γ_0, γ_1, γ_2, γ_3, γ_4 and γ_5 are parameters to be estimated. After estimating these parameters, we input them in the 1996 and 2014 samples. Then, we have a permanent fathers' and sons' labor income measure, given by the formula:

$$\hat{Y}_{if,1996/2014} = \hat{\gamma}_{0,1976/1995} + \hat{\gamma}_{1,1976/1995} \times S_{if} + \hat{\gamma}_{2,1976/1995} \times Ocup_{if} + \hat{\gamma}_{3,1976/1995} \times Black_i + \hat{\gamma}_{4,1976/1995} \times 35 + \hat{\gamma}_{5,1976/1995} \times 35^2 \quad (6)$$

$$\hat{Y}_{i,1996/2014} = \hat{\gamma}_{0,1996/2014} + \hat{\gamma}_{1,1996/2014} \times S_i + \hat{\gamma}_{2,1996/2014} \times Ocup_i + \hat{\gamma}_{3,1996/2014} \times Black_i + \hat{\gamma}_{4,1996/2014} \times 35 + \hat{\gamma}_{5,1996/2014} \times 35^2 \quad (7)$$

Where S_{if} is the vector of individuals i fathers' schooling level and $Ocup_{if}$ is their matrix of fathers' dummies for occupational categories.

Welfare Function and Gini Changes Decomposition

Sen (1970) defined the social welfare index as a function of income and inequality:

$$\ln W_t = \ln \bar{Y}_t + \ln (1 - G_t) \quad (1)$$

Also, Jenkins and Van Kerm (2006) showed that the change in income inequality between two time periods for a same set of observations could be expressed in terms of two components, following the equations below:

$$\Delta G = G(X_t) - G(X_{t-1}) = R - P \quad (2)$$

Where $G(X_t)$ as the Gini coefficient of a distribution in t, P represents the progressivity (pro-poorness) of income growth, and R representing reranking, both defined by:

$$R = G(X_t) - C(X_{t-1}, X_t) \quad (3)$$

$$P = G(X_{t-1}) - C(X_{t-1}, X_t) \quad (4)$$

Where where $C(X_{t-1}, X_t)$ is the Concentration coefficient of period t incomes against period t-1 ranking.
Now, in order do consider the impact of intergenerational mobility of occupations on welfare, I simulate sons' permanent earnings if they had their fathers' occupational category. Adapting Medeiros et al. (2018), I make three simulations with different responses on returns due to the lack of change in occupational composition.
1: All changes in occupational returns were demand-driven, so even with intergenerational immobility of occupations, the relative returns would be the same as in the observed sample. **2**: All changes in occupational returns were supply-driven, so intergenerational immobility of occupations would maintain sons' occupational returns at the same levels of fathers'. **3**: Changes in returns were 50% demand-driven and supply-driven, so sons' occupations coefficients on income will be the average of theirs in the observed sample and their fathers'.

Simulations results for Intergenerational Immobility of Occupations

In Tables below, each scenario i is denoted as "ci". The outcomes from the observed sample are denoted as "o", and the difference from observed and simulated outcomes is denoted as "(o-ci)".

Table 4: Growth and Inequality with Simulations of Intergenerational Immobility of Occupations

	$\ln Y_t - \ln Y_{t-1}$	$\ln(1-G)_t - \ln(1-G)_{t-1}$	$\ln W_t - \ln W_{t-1}$
1996o	0.096	0.008	0.105
1996c1	-0.105	-0.009	-0.114
1996(o-c1)	0.202	0.017	0.219
1996c2	-0.202	0.022	-0.180
1996(o-c2)	0.298	-0.013	0.285
1996c3	-0.155	0.008	-0.147
1996(o-c3)	0.252	0.000	0.252
2014o	0.441	0.224	0.665
2014c1	0.344	0.217	0.560
2014(o-c1)	0.097	0.007	0.105
2014c2	0.582	0.164	0.746
2014(o-c2)	-0.141	0.060	-0.081
2014c3	0.460	0.191	0.651
2014(o-c3)	-0.019	0.033	0.014

Note: the suffix 'o' represents the estimates and calculations from observed distribution of occupations, while the suffix 'c' represents the the ones from counterfactual distributions. Finally, '(o-c)' represents the differences from observed and counterfactual distributions.
Source: Estimates from PNAD 1976, 1995, 1996 and 2014

Table 5: Decomposition of Gini Variation by R and P Components

	P-component	-(R-component)	Gini Decrease
1996o	0.131	-0.126	0.005
1996c1	0.044	-0.048	-0.004
1996(o-c1)	0.087	-0.078	0.009
1996c2	0.059	-0.046	0.013
1996(o-c2)	0.072	-0.032	-0.008
1996c3	0.052	-0.046	0.006
1996(o-c3)	0.079	0.014	-0.001
2014o	0.256	-0.118	0.138
2014c1	0.179	-0.047	0.132
2014(o-c1)	0.077	-0.071	0.006
2014c2	0.137	-0.041	0.096
2014(o-c2)	0.119	-0.03	0.042
2014c3	0.158	-0.042	0.116
2014(o-c3)	0.098	0.012	0.022

Note: the suffix 'o' represents the estimates and calculations from observed distribution of occupations, while the suffix 'c' represents the the ones from counterfactual distributions. Finally, '(o-c)' represents the differences from observed and counterfactual distributions.
Source: Estimates from PNAD 1976, 1995, 1996 and 2014

The results show that, for the first period, income growth would fall drastically with I.I.O. in any scenario. On the other hand, Gini would not change much from the observed sample.
For the second period, while Gini decrease was higher in observed sample than in any simulation, income grows faster in scenario 2 and 3, in the first of both to the point of compensating the loss of Gini decrease, resulting in a higher increase of welfare index.
Table 5 exposes Gini change decomposition. For all simulations, both P and R decrease, showing that mobility of occupations is accountable for a higher β-Convergence and a larger extent of leapfrogging.