Assessing Implicit Redistribution in the Brazilian Social Security System[1]

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Resumo

Este artigo estuda o impacto de programas de seguridade social na distribuição da renda proveniente de empregos formais no Brasil. Através de técnicas de microssimulação, trajetórias de emprego com carteira assinada e salários são simuladas para uma amostra grande de indivíduos. Os resultados das simulações indicam que o sistema de proteção social brasileiro é redistributivo e progressivo, mas o impacto na diminuição da desigualdade parece ser limitado se comparado com outros países latino-americanos.

Palavras-chave: Redistribuição, Seguridade social, Seguro desemprego, Previdência, Microssimulação.

Abstract

This paper assesses the impact of social security programs on the distribution of lifetime formal labor income in Brazil. Using micro-simulation techniques, lifetime working histories are simulated for private sectors employees. The simulation results suggest that the system is progressive and also redistributive, even though the impact on inequality is somewhat limited when compared to other Latin-American countries.

Keywords: Redistribution, Social Security, Unemployment benefits, Micro-simulation.

JEL Codes: H55, J14, J26

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[1] This document is part of a five country-case studies conducted simultaneously using similar

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1 Introduction

Especially in Latin America, Social Security programs designs seek redistribution, which can be explicit or implicit. However, most of the times these programs also have non-predicted or undesired impacts on incentives, income and labor supply and demand, thus affecting redistribution in non-trivial manners.

This paper analyzes the impact of unemployment insurance and pension programs on the distribution of lifetime formal labor income in Brazil. It is part of a broader study carried on in five Latin American countries (Argentina, Brazil, Chile, Uruguay and Mexico). Using longitudinal survey data, econometric models of contributions to social security and labor income are estimated and Monte Carlo simulations of expected life time labor income and net transfers to social security are ran. The simulated results are then used to analyze the distribution and redistribution of formal income. The main finding is that the Brazilian social protection programs discussed in this paper are progressive but poorly targeted, resulting in a small decrease in inequality.

One of the main concerns in the recent literature is the failure of social security systems in covering the entire labor force (see, for instance, Robalino et al, 2011). Most of the time, the programs are exclusive for formal sector employees, which normally are better off than informal sector workers (Rofman et al. 2008). On the other hand, these same groups are the ones that pay more taxes, so the net effect is not clear (Forteza and Rossi, 2009).

Another potential source of redistribution failure might be in the fact that low densities of contribution can lead to ineligibility for benefits. This is even more important as low income workers have particularly low densities of contribution (Forteza et al. 2009; Berstein et al. 2006). In this research project, the focus lies on this last problem. Normally, redistribution within Social Security systems are analyzed comparing the taxes paid and benefits received by different groups of contributors, showing large transfers among groups which that depend on the ratio of beneficiaries to earners within each group. But most individuals move from contributor to beneficiary along the lifecycle. Thus, social security redistribution can be better assessed adopting a lifetime perspective (Liebman, 2001 and Forteza, 2011).

The methodology adopted in this study is micro-simulation. Because of this choice, the focus will be on intra-generational redistribution, assessing the transfers and progressivity of the system, but it should be noted that social security also allows for substantial inter-generational redistributions (Morató and Musto, 2010). Also, even though in this paper the unit of analysis is the individual, one must take into account that the net redistribution of any social protection system might look different at the family level (see Gustman and Steinmeier, 2001; Lambert 1993, p 14; and Brown et al., 2009).

According to Forteza (2011), the "ideal assessment of the redistributive impact of social security programs should be based on the comparison of income distribution with and without social security. This is not the same as comparing pre- and post-social security income (i.e. income minus contributions plus benefits), because social security is likely to induce changes in work hours, savings, wages and interest rates". For this, behavioral models need to be solved. Two examples of such models for Brazil can be found in

Robalino et al (2009) and Robalino, Zylberstajn and Robalino (2011). But, again according to Forteza (2011), "one possible drawback of these models is the assumption of full rationality, something that has been subject to much controversy, especially regarding long run decisions like those involved in social security. After all, the most appealed rationale for pension programs is individuals' myopia". To overcome this caveat, Forteza (2011) suggests a model with hyperbolic preferences, but solving and calibrating these models is not an easy task.[3]

The remainder of this paper is organized as follows. In the next section we briefly describe the programs to be analyzed. In sections three and four we describe the data and methodology. Section 5 presents the results and section 6 concludes.

2 The Brazilian old-age pension and unemployment insurance programs

According to Robalino et al (2009), Brazil spends around 12 percent of GDP on social insurance programs. These programs range in a large variety of designs and objectives, such as old-age, disability and survivorship pensions (RGPS benefits), insurance for work accidents, transfers related to maternity and sickness leave as well as non-contributory transfers to the elderly poor and disabled, unemployment insurance (UI) and a mandatory system of funded unemployment individual savings accounts (FGTS). It is crucial to mention that all these programs are exclusive for formal sector employees. These workers are defined as formal because their employers must sign a working card (*carteira de trabalho*) when hiring and this document is sufficient to claim UI and pension benefits.

The systems are quite complex, both in terms of contribution and benefits claiming rules. The RGPS is financed by social security contributions (8–11 percent depending on the income level) and payroll taxes (20 percent for most employers) and UI benefits are financed by a share of a 0.65 percent tax on gross revenues (case of the services sector) and a 1.65 percent tax on value added (case of the industrial sector). The FGTS also uses a payroll tax (8 percent) plus a dismissal fine of 40 percent of accumulated assets. These assets can only be cashed on dismissal or a few other exceptions such as death, severe disease or housing funding.

In terms of benefits eligibility, the RGPS alone has three regimes that depend on the retirement age and the vesting period: (i) retirement based on a minimum age (53 for men/48 for women) and a minimum number of years of contributions (30M/25W), paying a proportional length of contribution pension; (ii) retirement based on a number of years of contributions (35M/30W) and no minimum age; and (iii) retirement based on age (65M/60W) and a minimum number of years of contributions (15M/15W) that pays an Aging Pension. In the simulations carried on in this study, only the second and third regimes will be considered for simplicity.

[3] For a complete discussion on the advantages of the approach used in this study and some of the drawbacks, see Forteza (2011)

Regardless of the retirement regime, the system guarantees that the minimum pension (*Piso Previdenciário*) is equal to the minimum wage.[4] Robalino et al (2009) report replacement rates for the median and the average full-career worker between 40 and over 100 percent depending on the retirement age and the vesting periods. Detailed discussions on incentives for early and delayed retirement are found in Queiroz (2005), Queiroz (2007) and Robalino et al (2009).

As stated in the beginning of this section, formal sector workers who lose their jobs may count on two different income protection schemes. After a certain number of months of contributions, workers become eligible for an unemployment insurance benefit and the lump sum payment from their FGTS accounts. To be eligible for unemployment insurance, workers need to have held a formal sector job for at least 6 months in the previous 36-month period. With 6 to 11 months of contributions, workers receive 3 months of benefits; with 12 to 23 they receive 4 months; and with 24 to 36 they are eligible for 5 months of benefits. The benefit itself depends on earnings and range between the minimum wage and R$ 1,019.70 in 2011.

In case of dismissal without cause, along with UI formal sector workers receive a lump sum equal to the balance accumulated in their FGTS accounts while working in their last job plus a dismissal fine equal to 40 percent of the accumulated assets. However, the FGTS system will not be included in the redistribution analysis basically because it consists of an individual savings account fully funded by the workers current employment.

Robalino et al (2009) also report that the replacement rates offered by the unemployment insurance (UI) system range between 40 and 100 percent depending on the level of income. The authors state that when both UI and FGTS are considered together, the median worker can finance between 3.5 and 8 months of salaries depending on the number of months of contributions.

In terms of incentives the evidence can be classified as mixed. Some studies suggest that UI does not have a major impact on the duration of unemployment spells and, if anything, it allows workers to find better jobs (Margolis 2008). Previous analysis also found that UI does not significantly affect unemployment spells, except for those transiting into self-employment. Spells in this case are shortened (see Cunnigham 2000). Zylberstajn and Ribeiro (2010) found that the higher the benefits, the higher are the probabilities of job losses for married women and single men, but found no evidence for either married men or single women.

[4] The Brazilian pension system also offers an essentially flat pension equal to the minimum wage to workers in rural areas (eligibility ages are 60M/55F) and to the elderly poor (BPC). These schemes, however, are not analyzed here. For an analysis of the impact of the rural pension on labor supply and retirement age, see Carvalho-Filho (2008). Finally, there is a ceiling of around 340 percent of average earnings to the employee contribution and benefits.

3 Data

The *Pesquisa Mensal de Emprego* (PME), or Monthly Employment Survey, is a monthly rotating panel of dwellers in six major metropolitan areas in Brazil (*São Paulo, Rio de Janeiro, Belo Horizonte, Salvador, Porto Alegre* and *Recife*), compiled by IBGE (*Instituto Brasileiro de Geografia e Estatística*). These six metropolitan areas regions cover approximately 25% of the country's population. The PME survey was redesigned in March, 2002. Currently, microdata is available since then until April, 2011.

The survey investigates schooling, labor force, demographic, and earnings characteristics of each resident aged 10 or more that lives on the interviewed households. This results in approximately 100,000 individuals from 35,000 households every month. One important feature is that there is no information on earnings not related to labor supply.

The rotating scheme is as follows. Households are interviewed once per month during four consecutive months after which they stay out of the survey for an eight-month window. After this period, the household is interviewed again in four consecutive months. Once this last spell is finished, the household is permanently excluded from the sample. Households are divided into 4 rotating groups, in order to make sure that in two consecutive months 75% of the sample is the same.

The *PME* does not identify individuals directly, only their households. Thus, a matching process needs to take place. We match individuals within households over time using date of birth and gender, but one needs to bear in mind that there might be some attrition. Indeed, according to Ribas and Soares (2010), on average 4% of the households sampled in the PME do not answer to the survey in the following month. In order to avoid (or at least minimize) a selection bias, the authors propose an algorithm and the inclusion of an 'answering probability estimator' in an estimation a la Heckman.

In order to build the database, we match individuals (using the algorithm proposed above) that were surveyed for two consecutive months and consider this matching as one observation. Characteristics such as income, gender, age, marital status and schooling are taken from the first interview (identified by *t*), together with labor status. The subsequent interview (identified by *t+1*) gives only the new labor status and income.

The sample we work with includes only individuals that have been observed at least four times and that at least in one occasion have declared themselves as employed or unemployed. We work only with private sector employees or unemployed individuals.

Tables 1 and 2 present some descriptive statistics of the database.

Table 1 – Number of individuals that contribute to social security and contribution status

	Contributed at least once	Never contributed	% of individuals contributing
Male	229,385	180,908	40.74%
Female	172,164	202,777	31.00%
Total	401,549	383,685	36.09%

Source: Author calculation based on PME/IBGE

Table 2 – Number of interviews

		Male		Female	
		Contributed at least once	**Never contributed**	**Contributed at least once**	**Never contributed**
# of nterviews	4	40.7%	46.7%	40.4%	42.6%
	5	4.9%	4.8%	5.1%	4.5%
	6	5.6%	5.0%	5.9%	5.0%
	7	8.7%	7.3%	9.1%	7.8%
	8	40.2%	36.2%	39.4%	40.1%

Source: Author calculation based on PME/IBGE

4 Methodology

This section describes the following five steps of the methodology: (i) Estimation of contribution status model, (ii) estimation of labor income model, (iii) computation of social security contributions and pensions, (iv) computation of pre- and post-social security lifetime income and (v) computation of income distribution indexes.

4.1 Contribution status model

I begin by estimating the contribution status using a random effect linear probability model. The estimation could have been done using a fixed effects model, but because of the short number of periods, individual effects would be biased. The main advantage of these models is that they allow using the estimated individual effect to make predictions for the entire lifetime.

For the second to the last times individual i is observed, I estimate the following equation:

$$C_{it} = x'_{it}(1 - C_{i,t-1})\beta^0 + x'_{it}C_{i,t-1}\beta^1 + \eta_i + \varepsilon_{it} \qquad (1)$$

where C_{it} is a dummy variable equal to 1 if individual i contributed and zero otherwise.

Equation (1) is estimated by pool OLS, so the individual effects η_i are recovered as:

$$\hat{\eta}_i = \frac{\sum_{t=2}^{T_i}\left(C_{it} - x_{it}'(1-D_{it})\hat{\beta}^0 + x_{it}'D_{it}\hat{\beta}^1\right)}{(T_i - 1)}$$

For the first time individual *i* is observed, I estimate the following equation:

$$C_{i1} = x_{i1}'\gamma + \hat{\eta}_i + \epsilon_{i1} \qquad (2)$$

Note that the individual effect computed in the dynamic equation is used as a regressor in equation (2). The estimations results are presented in tables 3 and 4.

Table 3: First-period contribution status estimation

Equation (2): $D_{i1} = x_{i1}'\gamma + \hat{\eta}_i + \epsilon_{i1}$

	Male	**Female**
Age	0.093***	0.061***
	(0.002)	(0.002)
Age^2	-1.988***	-1.292***
	(0.045)	(0.038)
Age^3	1.222***	0.783***
	(0.035)	(0.030)
Education 2 (+)	0.045***	0.029***
	(0.003)	(0.002)
Education 3 (++)	0.102***	0.055***
	(0.003)	(0.003)
Education 4 (+++)	0.166***	0.192***
	(0.002)	(0.002)
η_i	1.386***	1.389***
	(0.010)	(0.010)
Unemployment rate	-0.014***	-0.011***
	(0.000)	(0.000)
Constant	-0.769***	-0.491***
	(0.022)	(0.019)
Adjusted R^2	0.162	0.155
N	410,293	374,941

(+) Between 4 and 7 years of schooling
(++) Between 8 and 10 years of schooling
(+++) 11 or more years of schooling
Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Second and following-period contribution status estimation

Equation (1): $C_{it} = x_{it}'(1-D_{it})\beta^0 + x_{it}'D_{it}\beta^1 + \eta_i + \varepsilon_{it}$

	Male	Female
(1-D)*Constant	0.012**	0.041***
	(0.005)	(0.004)
(1-D)*Age	0.009***	0.004***
	(0.000)	(0.000)
(1-D)*Age^2	-0.234***	-0.111***
	(0.007)	(0.006)
(1-D)*Age^3	0.156***	0.075***
	(0.005)	(0.005)
(1-D)*Education 2	0.010***	0.007***
	(0.001)	(0.001)
(1-D)*Education 3	0.024***	0.009***
	(0.001)	(0.001)
(1-D)*Education 4	0.036***	0.034***
	(0.001)	(0.001)
(1-D)*Unemployment Rate	-0.005***	-0.004***
	(0.000)	(0.000)
D*Constant	0.593***	0.636***
	(0.010)	(0.012)
D*Age	0.018***	0.012***
	(0.001)	(0.001)
D*Age^2	-0.320***	-0.168***
	(0.020)	(0.026)
D*Age^3	0.140***	0.024
	(0.016)	(0.021)
D*Education 2	0.011***	0.014***
	(0.002)	(0.002)
D*Education 3	0.021***	0.022***
	(0.002)	(0.002)
D*Education 4	0.042***	0.065***
	(0.001)	(0.002)
D*Unemployment Rate	-0.001***	-0.001*
	(0.000)	(0.000)
Adjusted R^2	0.823	0.791
N	2,024,545	1,874,901

(+) Between 4 and 7 years of schooling
(++) Between 8 and 10 years of schooling
(+++) 11 or more years of schooling
Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Predictions according to equations (1) and (2) can only be computed for the individuals in the sample, i.e. individuals for which we can compute the individual effects. But the model is built to predict the labor income flow of "new" individuals. Since we are working with a sufficiently large dataset, we randomly draw 10,000 males and 10,000 females from the sample, set their age as 18 years old and then use this "new" database for the simulations. The advantage of this approach is that we easily replicate the real distributions of the individual effects, without the need to make any assumptions on the distribution function of this variable[5]. This new set of individuals will be referred to as the out-of-sample database from this point on. Predictions for these individuals are computed as follows:

$$\tilde{P}_{i1} = x'_{i1}\hat{\gamma} + \hat{\eta}_i \text{ , if t = 1}$$

$$\tilde{P}_{it} = x'_{it}(1 - \tilde{C}_{i,t-1})\hat{\beta}^0 + x'_{it}\tilde{C}_{i,t-1}\hat{\beta}^1 + \hat{\eta}_i\text{, if t} \geq 2$$

$$\tilde{C}_{it} = 1 \; if \;\; \tilde{P}_{it} > draw_{it} \text{ ; 0 } otherwise$$

where $draw_{it}$ is a realization from a uniform (0,1) distribution for each period t and $\tilde{C}_{it}$ is a dummy indicator of the predicted contribution status for individual i at time t.

4.2 Projection of labor income

Labor income is modeled in a similar way compared to contribution status. Again, we are interested in capturing individual effects that will be used in the simulations. It should be noted that only formal labor income is estimated (i.e. income conditional on contributing, or conditional on having a formal job), which means that other incomes, including informal sector and self-employed are not considered.[6]

As with contribution status, I estimate two wage equations. In the second and subsequent months of a spell of contribution wages are modeled using a dynamic equation, whereas in the first month of a contribution spell wages are modeled with a static equation. As explained before, our data set has at least four observations for each individual, which are recorded every month. Conditional on having been employed in the previous occasion individual i was surveyed, wages are assumed to be governed by the following stochastic process:

$$\ln w_{it} = \rho \ln w_{it-1} + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 age_{it}^3 + \beta_4 edu2_i + \beta_5 edu3_i + \beta_6 edu4_i + \nu_i + e_{it} \quad (3)$$

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[5] The implicit assumption here is that the distribution of the individual effect does not vary with age or cohort.

[6] Some of the methods used in this project are based on Forteza et al. (2009).

Where w_{it} is the relative wage; age_{it} is the age at time t; edu2, edu3 and edu4 are educational dummies and ν_i is a time invariant unobservable characteristic of individual i. The idiosyncratic shock e_{it} is assumed to be normally distributed with mean 0 and variance σ_{it}^2. As long as we expect w_{it} to be stationary we do not introduce any deterministic time trend in the equation.

The individual effect is computed as:

$$\hat{\nu}_i = \frac{1}{T}\sum_{t=1}^{T}\left(\ln w_{it} - \left(\hat{\rho}\ln w_{it-1} + \hat{\beta}_1 age_{it} + \hat{\beta}_2 age_{it}^2 + \hat{\beta}_3 age_{it}^3 + \hat{\beta}_4 edu2_i + \hat{\beta}_5 edu3_i + \hat{\beta}_6 edu4_i\right)\right) \quad (4)$$

We estimate equation (3) by pooled OLS, using a simple random effects model.

Conditional on individual *i* was included in equation (3), the second wage equation is applied to the first time individual *i* is survey and if reported as employed and contributing. The equation to estimate is as follows:

$$\ln w_{it} = \alpha_1 + \alpha_2 age_{i1} + \alpha_2 age_{i1}^2 + \alpha_3 age_{i1}^3 + \alpha_4 edu2_i + \alpha_5 edu3_i + \alpha_6 edu4_i + \hat{\nu}_i + e_{i1} \quad (5)$$

where the variables are defined as before, and $\hat{\nu}_i$ is the individual effect estimated with equation (4). For equation (5) we use the OLS estimator with the White formula in order to obtain the standard errors. It must be noted that the introduction of the term $\hat{\nu}_i$ in equation (5) is a non-standard practice that should be considered with caution. The estimation results are shown in table 5. All coefficients have the expected signs and magnitudes, and the most interesting and important result is the significance and relevance of the individual effect in the first period equation.

Table 5 – Wage equations

	Male		Female	
	Eq. (1)	**Eq. (3)**	**Eq. (1)**	**Eq. (3)**
$Wage_{t-1}$	0.898***		0.908***	
	(0.001)		(0.001)	
Age	0.009***	0.104***	0.011***	0.096***
	(0.001)	(0.003)	(0.001)	(0.007)
Age^2/1,000	-0.139***	-1.503***	-0.209***	-1.636***
	(0.014)	(0.085)	(0.017)	(0.201)
Age^3/100,000	0.067***	0.702***	0.140***	0.921***
	(0.011)	(0.071)	(0.014)	(0.170)
Education 2 (+)	0.018***	0.178***	0.009***	0.102***
	(0.001)	(0.005)	(0.001)	(0.005)
Education 3 (++)	0.037***	0.342***	0.023***	0.277***
	(0.001)	(0.005)	(0.001)	(0.006)
Education 4 (+++)	0.085***	0.783***	0.072***	0.760***
	(0.001)	(0.005)	(0.002)	(0.006)
v_i		1.163***		1.075***
		(0.047)		(0.085)
Constant	-0.270***	-2.862***	-0.268***	-2.787***
	(0.008)	(0.039)	(0.009)	(0.085)
Adjusted R^2	0.863	0.306	0.872	0.261
N	752,275	158,478	523,916	112,060

Eq. (3): $\ln w_{it} = \rho \ln w_{it-1} + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 age_{it}^3 + \beta_4 edu2_i + \beta_5 edu3_i + \beta_6 edu4_i + v_i + e_{it}$
Eq. (5): $\ln w_{it} = \alpha_1 + \alpha_2 age_{i1} + \alpha_2 age_{i1}^2 + \alpha_3 age_{i1}^3 + \alpha_4 edu2_i + \alpha_5 edu3_i + \alpha_6 edu4_i + \hat{v}_i + e_{i1}$
(+) Between 4 and 7 years of schooling
(++) Between 8 and 10 years of schooling
(+++) 11 or more years of schooling
Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

The monthly labor income stream of the newborn individuals is thus computed using the following equations:

$$\ln \widetilde{w}_{it} = \hat{\alpha}_1 + \hat{\alpha}_2 age_{i1} + \hat{\alpha}_2 age_{i1}^2 + \hat{\alpha}_3 age_{i1}^3 + \hat{\alpha}_4 edu2_i + \hat{\alpha}_5 edu3_i + \hat{\alpha}_6 edu4_i + \hat{v}_i$$

$$\text{if } \tilde{C}_{it-1} = 0 \text{ and } \tilde{C}_{it} = 1$$

and

$$\ln \widetilde{w}_{it} = \hat{\rho} \ln \widetilde{w}_{it-1} + \hat{\beta}_1 age_{it} + \hat{\beta}_2 age_{it}^2 + \hat{\beta}_3 age_{it}^3 + \hat{\beta}_4 edu2_i + \hat{\beta}_5 edu3_i + \hat{\beta}_6 edu4_i + \hat{v}_i$$

for t > 1 and $\tilde{C}_{it-1} = 1$.

4.3 Social Security contributions and benefits

With the simulated work histories, it is straightforward to compute social security contributions, unemployment benefits and pensions. This is done according to the rules described in section 2. Both employee and employer contributions are considered, as both eventually impact on net wages in the long run (Gruber, 1999, p 90; Hamermesh and Rees 1993, p 212).

For simplicity, it is assumed that individuals claim benefits as soon as they become eligible.

4.4 Pre- and post-social-security lifetime income

Pre-social security lifetime labor income is the given by the present value of the expected simulated labor income:

$$\overline{W}(r) = \sum_{a=0}^{a=r-1} p(a)W(a)(1+\rho)^{-a}$$

Where r is age at retirement, $p(a)$ is the probability of worker's survival at age a, $W(a)$ is labor income at age a, and ρ is the discount rate (which was fixed at 3% per year in the simulations).

Post-social security income is given by the sum of present values of the retirement and UI flows:

$$PB = \sum_{a=r}^{a=\max\ age} p(a)B(a,r)(1+\rho)^{-a}$$

$$UB = \sum_{a=0}^{a=r-1} p(a)UB(a)(1+\rho)^{-a}$$

Where $\max age$ is maximum potential age, $B(a,r)$ is the amount of retirement benefits at age a conditional on retirement at age r, $UB(a)$ is the unemployment benefit collected at age a. Because of the assumption of no behavioral responses, the value of r is the same to compute the pre- and post-social security labor income. Also, this assumption implies that the interruptions in labor history are exogenous.

The indicator of social security transfer is the lifetime social security wealth, given by the present value of expected net transfers to social security:

$$SSW = PB + UB - SSC$$

$$SSC = \sum_{a=0}^{a=r-1} p(a)C(a)(1+\rho)^{-a}$$

Where $C(a)$ is the amount of contribution to social security at age a. SSC is the discounted flow of social security contributions. These formulas are similar to those used by Liebman (2001).

4.5 Income distribution indexes

In order to assess how much redistribution takes place within the social security system, five sets of indicators are used. First, the distribution of individuals' social security wealth and social security wealth-to-income ratios are computed. Second, social security wealth versus pre-social security labor income are plotted, following the procedure in Liebman (2001). Third, Lorenz curves of the expected pre-social security labor income and the associated concentration curves of the expected post-social security labor income (ranked by pre-social security income) are computed. Fourth, the Ginis of the pre- and post-social security labor income (with 95% confidence intervals) are calculated. Finally, the Reynolds-Smolensky-type index of net redistributive effect (Lambert, 1993, p 256) is also computed. According to Forteza (2011), "this index assesses the redistributive impact of a program computing the area between the Lorenz pre-program income and the concentration post-program income. A positive (negative) value indicates that the program reduces (increases) inequality".

The Lorenz and concentration curves, the Gini coefficients and the Reynolds-Somelinsky index were estimated using DASP (Araar and Duclos 2009).

5 Results

This section presents the results for both in- and out-of-sample simulations. First, table 6 shows the percentage of correct predictions[7] of contribution status in the sample. These values can serve as a goodness-of-fit measure.

Table 6 – In sample predictions

	Male	Female
Does not contribute	92.2%	94.0%
Contributes	89.8%	88.0%

Source: Simulation model

The out-of-sample simulations results are presented according to the five indicators described in the previous section. Before that, some statistics on the simulated years of

[7] Simulated status matches observed status

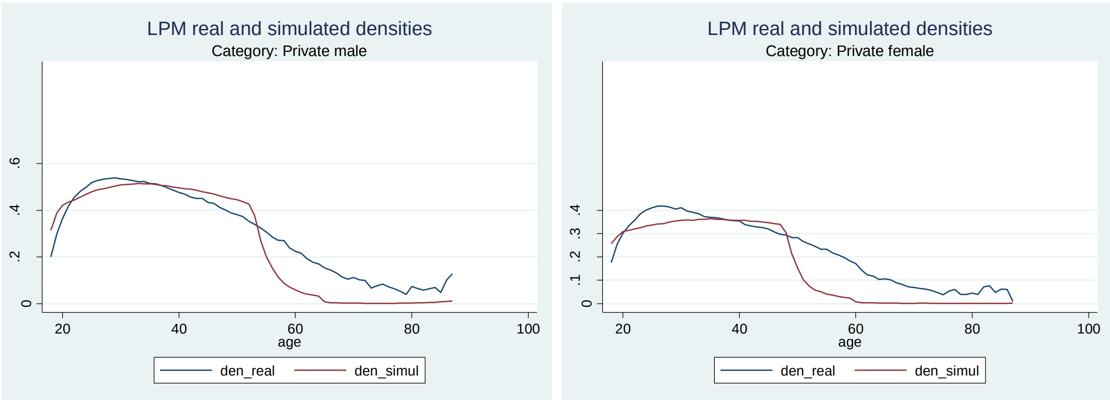
contribution, retirement age and percentage of individuals that have access to pensions are shown below, as well as the simulated and observed contribution densities.

Table 7 – Retirement statistics for simulated population

	Male	Female
Average years of contribution	17.5	11.0
Average retirement age	57.3	51.4
% of individuals that access pensions	47.6%	35.4%

Source: Simulation model

Figure 1 – Simulated and observed contribution densities



Source: Simulation model and PME/IBGE

Next, I begin with the pre-social security lifetime labor income and social security wealth distributions. As shown in table 8, the lowest value of labor income is zero, meaning that for some individuals the contribution status is never achieved[8]. The median worker has an expected lifetime formal labor income present value of 48,100 US dollars, while the 99th percentile individual would have an expected income of 1,533,500 dollars. The average lifetime income is 143,300 dollars. On the other hand, social security wealth is negative for both the P1, median and average worker, while slightly positive to the P99 individual. The dispersion found in the difference between P1 and P99 social security wealth is expected in a PAYG-DB system, but the high contribution rates faced both by employers and employees are the main reason for such a high difference. Studies have shown that the actuarial neutral contribution rate for pensions in the private sector in Brazil would be around 17% (Giambiagi and Afonso, 2009), but rates are close to 30% in the current design. Moreover, unlike in other Latin American countries, there is no ceiling on the employer's contribution (as mentioned before, it is 20% of the salary), but there is a maximum benefit value. For lower percentile workers, though, the ratio SSW-to-income can be as high as 196%, while for the median worker it is -6% and for the P1 worker it is -30%. These results indicate that the system is redistributive, since higher percentile

[8] This result can also be due to the small periods observed in the survey

workers contribute with more than what they receive from the system, while the opposite happens to the lowest percentiles workers.

Table 8 – Pre-social security lifetime labor income and social security wealth (in thousands of 2010 US dollars)

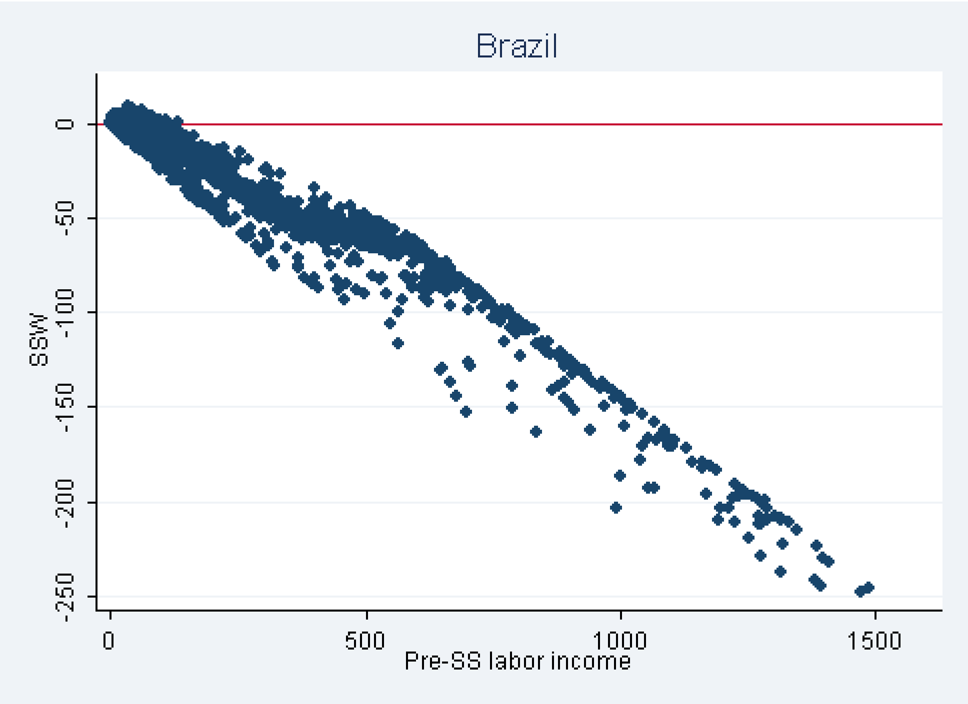
	Mean	P1	Median	P99	Skewness
Income	143.3	0.0	48.1	1533.5	22.3
SSW	-19.8	-258.2	-2.4	4.2	-23.4
SSW/Income	6%	-30%	-6%	196%	3.2

Source: Simulation model

The results shown so far indicate that there is potential to a large redistribution within the system. This redistribution, however, depends also on how the transfers are correlated to lifetime income. One must remember that a large share of the workers never contribute, thus being ineligible for old age pensions or unemployment benefits.

To this extent, figure 1 plots SSW versus pre-social security lifetime labor income. The SSW axis is limited to US$ -250,000, but there may exist some extreme values much higher than this (see table 8 and remember there is no lower bound for the employer's contribution). The negative slope of the curve indicates that the system is indeed progressive. Moreover, figure 2 also seems to indicate that there is redistribution, because for a fixed level of labor income one finds different levels of social security wealth. However, the dispersion of the cloud around the curve also indicates that individuals may get lower SSW despite of being poorer than others, which would lead one to conclude that there is, at least to some extent, poor targeting on the system. Liebman (2001) reports a similar finding for the US.

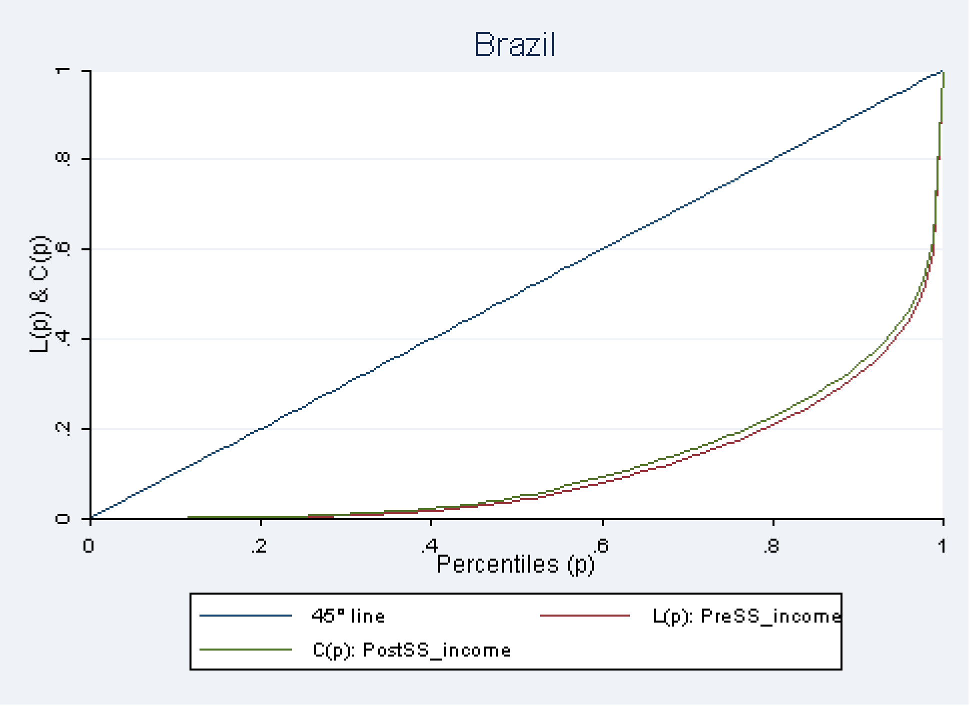
Figure 2 - Social security wealth and life time income



Source: Simulation model

Figure 3 presents the Lorenz curves of pre-social security labor income and the concentration curves of post social security labor income. The fact that the post-social security income curve is above the pre-social security line indicates that, although small, social security programs induce some equalization.

Figure 3: Pre Social Security life time labor income Lorenz curve and post Social Security life time income concentration curve



Source: Simulation model

The Gini coefficients are shown in table 9. The simulated pre-SS lifetime labor income has a value of 0.76, indicating that the income considered in the estimation is considerably more unequal than current reported income in PNAD, the annual household survey. CEDLAS and The World Bank (April 2011), for example, report a Gini coefficient for household per capita income of 0.537 for Brazil. Still, it must be noted that this indicators is not comparable to the one presented in this study, to the extent that the Gini estimated by the model presented in this study refers to individual lifetime formal labor income, whereas the Gini reported by CEDLAS and The World Bank refers to total household per capita as opposed to household per capita income, to labor as opposed to total (formal plus informal) current income.

The simulations indicate that the social security system causes a reduction slightly higher than two points in the Gini coefficient. However, the 95% confidence interval for both measures overlap. Thus, this result must be considered with caution. The Reynolds-Smolensky index, however, is significant at 1% and its estimate is 1.98% (with standard error of 0.00028).

Table 9: Gini coefficients of life time labor income before and after social security

	Gini before SS	Gini after SS
Estimate	0.7630	0.7435
Lower confidence bound (95%)	0.7412	0.7214
Upper confidence bound (95%)	0.7848	0.7655

Source: Simulation model

6 Concluding Remarks

The results presented in this paper, which was part of a broader study involving five different countries in Latin America, shows that the Brazilian old-age pension and unemployment insurance schemes for private sector workers are progressive and redistributive. By micro-simulating histories of contribution status and formal labor income, it was possible to calculate contributions and benefits and, subsequently, compute the individual expected lifetime transfers to social security. Afterwards, lifetime redistribution was computed as the dispersion of the social security wealth and the social security wealth to pre-social security income ratios. The difference between the percentiles 99 and 1 of social security wealth is about 260 thousand dollars in Brazil.

In terms of inequality, the Gini coefficient is reduced in two points when social security transfers are considered. However, the size of the inequality reduction is not large, despite the huge amount of redistribution and the progressivity of the programs. For the sake of comparison, Forteza (2011) summarizes the findings of other studies that used a similar methodology to the one presented here and the Gini falls are roughly 3.8 points in the case of Chile and 1.8 points in Uruguay. In Mexico there is no significant change in the coefficient (the system is supposed to be actuarially fair) and in Argentina there is a small increase in inequality (Gini moves from 0.5504 to 0.5638). On all these countries, however, total contributions to the social security systems are much smaller when compared to the Brazilian case.

It is important to highlight that the only source of income considered in the simulations is from formal sector jobs. Thus, the impact on inequality can be even smaller, since low income workers tend to have higher informal income. Possible policy implications would include a better targeting of the transfers made within the system.

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