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ECONOMIC INTEGRATION, POVERTY AND REGIONAL INEQUALITY IN BRAZIL

by

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ABSTRACT

Gains and losses from trade liberalization are often unevenly distributed inside a country. For example, if budget shares vary according to household income, changes in commodity prices will redistribute an overall welfare change between household types. Household incomes will also be differentially affected. Sectoral differences in factor-intensity mean that changes in industrial structure cause redistribution of income between primary factors. Particular primary factors (such as capital, or less skilled labour) may contribute disproportionately to the incomes of certain household types. The fortunes of such households indirectly depend on the prospects of particular sectors.

We emphasize these distributive issues, especially those arising from the income side. At the same time we distinguish households by regions (within the country). The regional distinction sharpens the contrast between groups of households. Particular regions have their own patterns of economic activity and so are differently affected by changes in the industrial protection structure. Since regional household incomes depend closely on value-added from local industries, economic change will tend to redistribute income between regional households. If the regional concentration of poverty is more than we could predict by regional primary factor endowments and industry structure, the addition of a regional dimension will add power to our analysis of income distribution beyond the mere addition of interesting regional detail.

The paper deals with these issues more fully. We extend previous regional modeling of Brazil to include the intra-household dimension, addressing poverty and income distribution issues that may be caused by trade integration. An applied general equilibrium (AGE) inter-regional model of Brazil underlies our analysis, with a detailed specification of households. The model is static and solved with GEMPACK. The Representative Household (RH) hypothesis is abandoned; instead a micro-simulation (MS) model is used to track changes in household income and expenditure patterns.

This micro-simulation model is built upon two Brazilian household studies: (1) the Household Budget Survey (POF, IBGE, 1999) covers detailed expenditure patterns for 16,013 households and 11 regions in Brazil in 1996; (2) the National Household Sample Survey (PNAD, IBGE, 1997) is a yearly survey that includes detailed information about household employment and income sources, with 331,263 observations. We integrate the two data sources to produce a detailed mapping of expenditure and income sources for 112,055

Brazilian households and 263,938 adults, distinguishing 42 activities, 52 commodities, and 27 regions.

We link the AGE and MS models together, solving them iteratively to get consistency between results. After a shock the AGE model communicates changes in wages and employment by industry and labour type to the MS model that individually simulates the changes in employment, income and expenditure patterns for each household. The new expenditure pattern is then communicated to the AGE model, and the process is repeated until the two models converge. The final results from the MS model enable us to estimate changes in poverty and income distribution measures, both nationally and for regions within Brazil.

We use the model to analyze poverty and income distribution impacts of the Free Trade Area of Americas formation upon the Brazilian economy. In the particular simulation we examine, freer trade leads to increased employment, especially for lower-paid workers. Poor households, which contain more unemployed adults, benefit most. This leads to a reduction in poverty in all 27 Brazilian states.

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ECONOMIC INTEGRATION, POVERTY AND REGIONAL INEQUALITY IN BRAZIL[1].

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1 Introduction

One of the most striking aspects of the Brazilian economy is its high degree of income concentration. Despite the changes the economy has faced in the last twenty years, ranging from the country's re-democratization, trade liberalization, hyperinflation, many currency changes, and finally, to the macroeconomic stabilization in the mid-nineties, the country still shows one of the worst patterns of income distribution in the world. The resilience of this income distribution problem has attracted the attention of many researchers all over the world, and is the central point of a lively debate in Brazil. The problem is, of course, extremely complex, related to a great number of socio-economic variables, which makes it a particularly difficult analytical issue, since the effects of many variables upon poverty are uncertain.

At the same time, new changes in the economic environment now challenge the Brazilian economy. Among them, the participation of the country in new free trade areas may be one of the most important. A complex phenomenon in itself, the economic integration poses new questions relating to the prospects for the poor. This paper is an attempt to address these questions with a systematic and quantitative approach. For this purpose, an applied general equilibrium model of Brazil tailored for income distribution and poverty analysis will be used. The model has also an inter-regional breakdown, which will make it possible to assess the regional inequality associated issue.

The plan of the paper goes as follows: the next section shows some figures about the problem of poverty and income distribution in Brazil, with a brief review of the recent literature on the topic. Then, we present the methodological approach to be pursued here, with a discussion of the relevant literature on the many different approaches. Then the model itself

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is presented, with a discussion of its main aspects and of the database. Finally, results and conclusions are presented.

2 Poverty and income distribution evolution in Brazil: an overview.

It has long been recognized that, although Brazil is a country with a large number of poor people, its population is not among the poorest in the world. Based on an analysis of the 1999 Report on Human Development, Barros et alii (2001) show that around 64% of the countries in the world have per capita income less than in Brazil, a figure that mounts to 77% if we consider the number of persons in the same condition. The same authors show that, while in Brazil 30% of the total population are poor, on average only 10% are poor in other countries with similar per capita income. Indeed, based on the same report the authors define an international norm that, based on per capita income, would impute only 8% of poor for Brazil. That is, if the inequality of income in Brazil were to correspond to the world average inequality for countries in the same per capita income range just 8% of the Brazilian population would be expected to be poor.

Taking the concept of poverty in its particular dimension of income insufficiency, the same authors show that in 1999 about 14% of the Brazilian population lived in households with income below the line of extreme poverty (indigence line, about 22 million people), and 34% of the population lived in households with income below the poverty line (about 53 million people). Even though the percentage of poor in the population has declined from 40% in 1977 to 34% in 1999, this level is still very high and, it seems, stable. The size of poverty in Brazil, measured either as a percentage of the population or in terms of a poverty gap, stabilizes in the second half of the eighties, although at a lower level than was observed in the previous period.

Barros and Mendonça (1997) have analyzed the relations between economic growth and reductions in the level of inequality upon poverty in Brazil. Among their main conclusions, these authors point out that an improvement in the distribution of income would be more effective for poverty reduction than economic growth alone, if growth maintained the current pattern of inequality. According to these authors, due to the very high level of income inequality in Brazil it is possible to dramatically reduce poverty in the country even without economic growth, just by turning the level of inequality in Brazil close to what can be observed in a typical Latin American country.

The poverty in Brazil has also an important inter-regional dimension. According to calculations due to Rocha (1998), in a study for the 1981/95 period, the South-East region of the country, while counting for 43.84% of total population in 1995 had only 33% of the poor. These figures were 15.37% for the South region (8.15% of poor), and 6.81% for the Center-West region (5.23% of poor). For the poorer regions, on the contrary, the share of population in each region is lower than the share of poor: 4.56% (9.32% of poor) for the North region, and 29.42% (44.31% of poor) for the North-East region, the poorest region in the country.

In terms of evolution of regional inequality, Rocha concludes that no regular trend could be observed in the period. Moreover, the author also concludes that the yearly observed variations in concentration are mainly related to what happens in the state of São Paulo (South-East region) and in the North-East region. This reinforces the position of these two regions in the extremes of the regional income distribution in Brazil. The author also points out that once the effects of income increase that followed the end of the hyper-inflation period in 1995 run out, the favorable evolution in the poverty indexes and its spatial incidence will depend mainly on the macroeconomic determinants related to investment. Also, the author concludes that even keeping unchanged the actual level of poverty, the reduction in the regional inequality will require the reallocation of industrial activity to the peripheral regions.

And, finally, the same author also concludes that the opening of the economy to the external market (mainly in relation to the formation of Mercosur) would help reduce regional inequality in Brazil. This would happen through reduced consumer prices in the poorest regions, which are fortunately lacking in the industries most threatened by new trade flows.

Green, Dickerson and Arbache (2001) analyzed the behavior of wages and the allocation of labor throughout the 1980-99 trade liberalization period in Brazil. Among the main findings the authors point out that wage inequality remained fairly constant for the 1980s and 1990s, with a small peak in the mid 80s. The main conclusion of the study is that the egalitarian consequences of trade liberalization were not important in Brazil for the period under analysis. As caveats, the authors note the low trade exposure of the Brazilian economy (around 13% in 1997), as well as the low share of workers that have completed college studies in total (1 in 12 workers at that time).

3 Methodology

Computable general equilibrium (CGE) models have long been used for poverty analysis. In the traditional analysis, however, the Representative Household formulation has been used to represent consumer behavior in the model. This formulation, although adequate for many purposes, limits our investigation of poverty and income distribution analysis. More recent approaches were developed to deal with these constraints.

Savard (2003) provides a lapidary discussion of the topic. According to that author, the models dealing with poverty and income distribution analysis can be classified into three main categories: models with a single representative household (RH), models with multiple-households (MH), and the micro-simulation approach that links a CGE model to an econometric household micro-simulation model.

The Representative Household model is the traditional method, and has been widely used in the literature. The main drawback of this model for income distribution and poverty analysis is that there are no intra-group income distribution changes, as the households are all aggregated into a representative one. This, of course, limits the scope for economic behavior in the model.

The second approach, the multiple-household model (MH), consists of multiplying the number of households. Increasing computation capacity allows us to have a large number of households in the model. To take an extreme case, the total number of households in a household survey could be used. This approach then allows the model to take into account the full detail in household data, and avoids pre-judgment about aggregating households into categories. The main disadvantages of this type of approach are that data reconciliation can be difficult, and that the size of the model can become a constraint.

The third approach, which we call MS, draws on micro-simulation techniques. Here, a CGE model generates aggregate changes that are later communicated to a micro-simulation model based on a large unit record database. Savard (2003) points out that the drawbacks to the approach are coherence between models, since the causality usually runs from the CGE model to the micro-simulation model, with no feedback between them.

The approach pursued in this paper takes advantage of the same general idea raised by Savard (2003) to overcome the difficulties posed by the three first options abovementioned: the use of a CGE model linked to a micro-simulation model, but with a bi-directional linkage between them that would guarantee a convergence of solution for both models. Savard links the models by running them in a repeated sequence of CGE-MS model runs, first computing the CGE simulation, then the MS model simulation, in a looping way, until convergence occurs. The main advantages of this approach are that: there is no obligation to scale microeconomic data to match the aggregated macro data; we can accommodate more households in the MS model; and the MS model may incorporate discrete-choice or integer behaviour that might be difficult to incorporate in the CGE model. The CGE model used here is a static inter-regional model of Brazil based on the ORANIG model of Australia (Horridge, 2000). This non-linear model is written in linearized form, solved with GEMPACK, and distinguishes between 42 sectors and 52 commodities[4]; 10 labor occupational categories; and 27 regions inside the country, using a top-down technology.

The CGE model was calibrated with data from the Brazilian economy for 1996, obtained from two main sources: the 1996 Brazilian Input-Output Matrix (IBGE. http://ibge.gov.br), and the Brazilian Agricultural Census (IBGE, 1996).

On the income generation side of the model, workers are divided into 10 different categories (occupations), according to their wages. These wage classes are then assigned to each regional industry in the model. Together with the revenues from other endowments (capital and land rents) these wages will be used to generate household incomes. We extend the CGE model to cover 270 different expenditure patterns, composed of 10 different income classes in 27 regions.

There are two main sources of information for the household micro-simulation model: the Pesquisa Nacional por Amostragem de Domicílios –PNAD (National Household Survey – IBGE, 2001), and the Pesquisa de Orçamentos Familiares- POF (Household Expenditure Survey, IBGE, 1996). The PNAD is an annual national survey that has been done since 1966. It contains information about households and persons, and shows a total of 331,263 records. The main information extracted from PNAD were wage by industry and region, as well as other personal characteristics such as years of schooling, sex, age, position in the family, and other socio-economic characteristics.

The POF, on the other hand, is an expenditure survey that covers 11 metropolitan regions in Brazil. It was undertaken during 1996, and covered 16,014 households, with the purpose of updating the consumption bundle structure. The main information we drew from this survey was the expenditure patterns of 10 different income classes, for the 11 regions. We assigned one such pattern to each individual PNAD household, according to each income class. As for the regional dimension, the 11 POF regions were mapped to the larger set of 27 CGE regions. Here it must be stressed that the POF survey just brings information about urban areas (the metropolitan areas of the main state capitals)[5].

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[4] One of the activities (Agriculture) produces 11 commodities.

[5] A new Brazil POF, covering both urban and rural areas, will probably be released late in 2004.

3.1 *Model running procedures and highlights.*

As mentioned before, our model consists of two main parts: a Computable General Equilibrium model (CGE) and a Household Model (MS). Our approach for the analysis consists in running the two models sequentially, whilst attempting to obtain consistency between them. The logical sequence of this procedure, as well as more details, is described in this section.

The process starts with a run of the CGE model. The trade shocks are applied, and the results calculated to 52 commodities, 42 industries, 27 regions, and 10 labor occupations. The results from the CGE model, then, are used to update the MS model. This update consists basically in updating wages and changes in labor demand, for the 263,938 workers in the sample. These changes have a regional (27 regions) as well as sector (42 industries) dimension.

In doing so, we followed two main approaches[6]. In the first approach, instead of relocating jobs according to changes in labor demands, the wage was updated with the total wage bill change in each occupation, region and sector. This change then summarizes variations both in wages and employment, and would be equivalent to having each worker that already has a job in the base year working more hours whenever an increase in labor demand occurs, and vice-versa.

The second approach takes a different route, and actually relocates jobs according to changes in labor demand. This is done changing the PNAD weights[7] of each worker (see Appendix for details) to mimic the change in employment. This procedure was called the "quantum weights method"[8]. In this second approach, then, there is a true job relocation process going on. If, as occasionally occurs, some region has insufficient unemployed workers in some occupational category, the already employed workers will increase the number of hours worked to meet the increasing labor demand. We will report results due to those two methods. Having updated the database, the expenditure results from the MS model are fed back into the CGE model, until the convergence of the results[9]. Once the final results are obtained, the change in poverty indexes are calculated and reported.

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[6] The methodology is described in more detail in the Appendix. Here we present only the main ideas.

[7] Each individual in the sample has a weight that vary according to the municipality where data was collected, and equals the ratio of actual households (in that municipality) to the number of interviewed households.

[8] Mark Horridge developed this method for this project.

[9] For the simulation in this paper, only 1 loop was needed to converge, since the changes in demands were small.

In any of the two approaches a new updated income matrix is generated, for the total number of records in the original database (PNAD). This post-simulation matrix has the same number of records as the original one (263,938), and keeps unchanged the original link between workers and households.

One final point about the procedure used in this paper should be stressed. Although the changes in the labor market are simulated for each adult in the labour force, the changes in expenditures and in poverty are tracked back to the household dimension. This is possible since PNAD has a key that links persons to household, that's to say, we know to which household each person belongs. Each household contains one or more adults, either working in a particular sector and occupation, or unemployed. In our model then it is possible to recompose changes in the household income from the changes in individual wages. This is a very important aspect of the model, since it is likely that changes in employment records are cushioned, in general, by this procedure. If, for example, one person in some household loses his job but another in the same household gets a new job, household income may change little, or not at all. Moreover, since households are the expenditure units in the model, we would expect household spending to be cushioned by this income pooling effect.

4 The base year picture

In this section we extend the above description of poverty and income inequality in Brazil. The reference year for our analysis is 2001. Some general aggregated information about poverty and income inequality in Brazil can be seen in Table 1.

The rows of Table 1 correspond to income classes, grouped according to POF definitions[10], such that POF[1] is the lowest income class, and POF[10] the highest. A fair picture of income inequality in Brazil emerges from the table. We see that the first 5 income classes, while accounting for 52.6% of total population in Brazil, get only 17% of total income. The highest income class, on the other hand, accounts for 11% of population, and about 45% of total income. The Gini index associated with the income distribution in Brazil

[10] POF[1] ranges from 0 to 2 minimum wages, POF[2] from 2+ to 3, POF[3] from 3+ to 5, POF[4] from 5+ to 6, POF[5] from 6-8, POF[6] from 8-10, POF[7] from 10-15, POF[8] from 15-20, POF[9] from 20-30, and POF[10] above 30 minimum wages. The minimum wage in Brazil in 2001 was around US$76.

in 2001, calculated using an equivalent household[11] basis, is 0.58, placing Brazil's income distribution among the world's worst.

Table 1. Poverty and income inequality in Brazil, 2001.

Income group	PrPop	PrInc	AveHouInc	UnempRate	PrWhite	AveWage	PrChild
POF[1]	10.7	0.9	0.1	32.6	35.2	0.2	46.2
POF[2]	8.0	1.8	0.4	17.3	38.3	0.3	37.2
POF[3]	16.0	5.2	0.6	10.4	42.0	0.4	35.1
POF[4]	7.3	3.1	0.8	8.8	45.1	0.4	32.5
POF[5]	11.0	5.8	1.0	7.5	49.2	0.5	28.7
POF[6]	7.9	5.1	1.2	7.4	53.4	0.6	26.4
POF[7]	12.9	11.1	1.7	6.8	60.3	0.8	24.5
POF[8]	7.5	8.7	2.3	6.1	66.3	0.9	21.5
POF[9]	7.7	12.7	3.1	5.9	71.2	1.4	20.5
POF[10]	10.9	45.7	7.9	4.2	81.6	3.2	17.7
Total	100.0	100.0	---	---	---	---	---

PrPop = % in total population; PrInc = % in country total income; AveHouInc = average household income; UnempRate = unemployment rate; PrWhite = % of white population in total; AveWage = average normalized wage; PrChild = share of population under 15 by income class.
Source: PNAD, 2001.

The unemployment rate is also relatively higher among the poorer classes. This is a very important point to be noted, due to its relevance for modeling. The opportunity to get a new job is probably the most important element driving people out of poverty: hence the importance for poverty modeling of allowing the model to capture the existence of a switching regime (from unemployment to employment), and not just changes in wages. As can be seen in Table 1 above, the unemployment rate reaches 36.5% among the lowest income group (persons above 15 years), and just 7.7% among the richest.

For the purpose of further describing the state of income insufficiency in Brazil we set a poverty line defined as one third of the average household income[12]. According to that criterion 30.8% of the Brazilian households in 2001 would be poor[13]. This would comprise

[11] The equivalent household concept measures the subsistence needs of a household by attributing weights to its members: 1 to the head, 0.75 to the other adults, and 0.5 to the children (eg, to feed 2 does not cost double).

[12] This poverty line is equivalent to US$ 48.00 in 2001.

[13] Barros et all (2001), working with a poverty line that takes into account nutritional needs, find that 34% of the Brazilian households were poor in 1999.

96.2%, 76.6% and 53.5% respectively of households in the first three income groups[14], or 34.5 million out of 112 million households in 2001.

The table below, which is further explained in Appendix section 9.3, shows how each POF group contributes to three overall measures of poverty:

- FGT0: the proportion of poor households (ie, below the poverty line)
- FGT1:the average poverty gap (proportion by which household income falls below the line)
- FGT2: measures the extent of inequality among the poor.

Table 2 POF group contributions to FGT poverty indices

POF group	% of all families	share below poverty line	average poverty gap	contributions to FGT0	contributions to FGT1	contributions to FGT2
POF[1] poorest	10.7	0.9617	0.7334	0.1122	0.0856	0.0715
POF[2]	8.0	0.7657	0.3047	0.0716	0.0285	0.0135
POF[3]	16.0	0.5355	0.1496	0.0877	0.0245	0.0092
POF[4]	7.3	0.2837	0.0539	0.0202	0.0038	0.0011
POF[5]	11.0	0.1143	0.0189	0.0122	0.0020	0.0005
POF[6]	7.9	**0.0390**	0.0054	0.0029	0.0004	0.0001
POF[7]	12.9	0.0082	0.0009	0.0010	0.0001	0.0000
POF[8]	7.5	0.0008	0.0001	0.0001	0.0000	0.0000
POF[9]	7.7	0.0000	0.0000	0.0000	0.0000	0.0000
POF[10] richest	10.9	0.0000	0.0000	0.0000	0.0000	0.0000
	sum=100	FGT0= ave=0.3079	FGT1= ave=0.1449	FGT0= sum=0.3079	FGT1= sum=0.1449	FGT2= sum=0.0960

As stated before, this general poverty and inequality picture also has an important regional dimension in Brazil. This is a consequence of the spatial concentration of economic activity, which is located mainly in the South-East region. This is particularly true of industrial activity; agriculture is more dispersed among regions. Table 3 shows more information about the regional dimension of poverty and income inequality in Brazil. The map, Figure 1, shows where regions are located, and shades them according to proportions of households in

[14] The proportion of households below the poverty line in the other income groups are 0.284% for the 4th, 0.14% for the 5th, 0.04% for the 6th, 0.008% for the 7th, and 0.001% for the 8th. There are no households below the poverty line for the two highest income classes.

poverty.

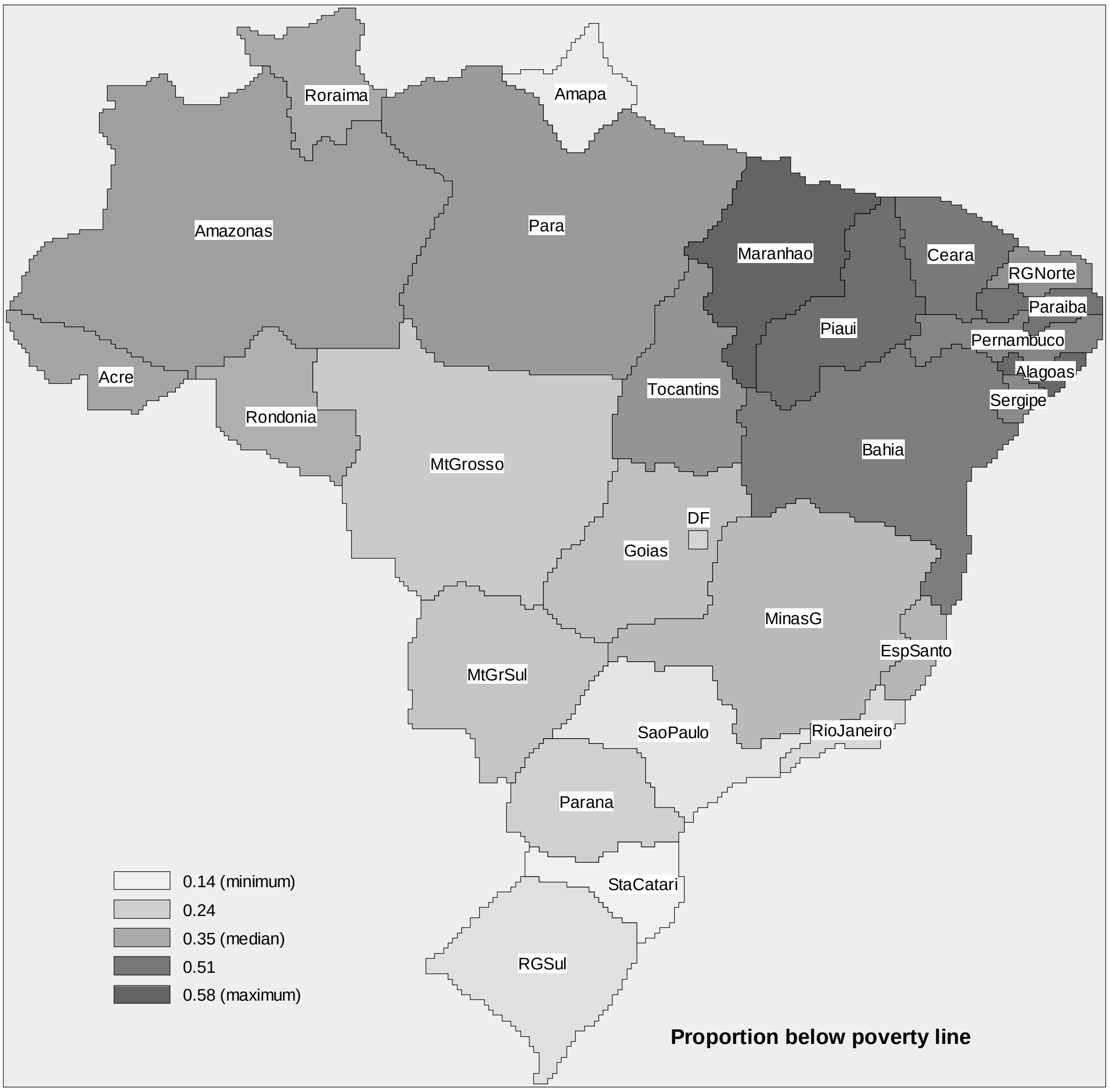

Figure 1: Brazil states shaded according to proportion in poverty

As can be seen in the Table, the states in the North region account for 8% of total population, compared to 23.5% for the North-East, 45% in the South-East, 16% for South, and 7.2% for the Center-West. In the SE region the state of São Paulo alone accounts for 22.9% of total Brazilian population.

The next column in Table 3 shows the share of households below the poverty line in each region, as a proportion of total regional households. As can be seen, the states in the NE region (states numbered from 8 to 15 in the table) plus the states of Tocantins and Para in the N region present the highest figures for this indicator, showing that these states are relatively poorer. If, however, regional population is taken into account, the third column show that the populous regions of Ceará, Pernambuco, Bahia, Minas Gerais and São Paulo give higher contributions to the Foster-Greer-Thorbecke poverty gap index[15]. These figures are the contribution of each state to the total poverty gap index in Brazil expressed as a proportion of the poverty line (see column total). We can see that the average poverty gap in Brazil in 2001 is a 14.5% insufficiency of income to reach the poverty line.

Table 3. Regional poverty and income inequality figures. Brazil, 2001.

Regions	Macro-regions*	Population share of each region	Proportion of poor households in regional population	Regional Contribution to the Poverty Gap	Regional Average Poverty Gap
1 Rondonia	N	0.005	0.338	0.001	0.147
2 Acre	N	0.002	0.356	0.000	0.176
3 Amazonas	N	0.011	0.396	0.002	0.196
4 Roraima	N	0.001	0.347	0.000	0.152
5 Para	N	0.023	**0.425**	0.005	**0.194**
6 Amapa	N	0.003	0.151	0.000	0.069
7 Tocantins	N	0.006	**0.429**	0.001	**0.180**
8 Maranhao	NE	0.029	**0.579**	0.008	**0.288**
9 Piaui	NE	0.015	**0.564**	0.005	**0.304**
10 Ceara	NE	0.042	**0.540**	**0.011**	**0.267**
11 RGNorte	NE	0.016	**0.471**	0.004	**0.218**
12 Paraiba	NE	0.019	**0.550**	0.005	**0.257**
13 Pernambuco	NE	0.045	**0.512**	**0.011**	**0.248**
14 Alagoas	NE	0.015	**0.577**	0.004	**0.289**
15 Sergipe	NE	0.010	**0.503**	0.002	**0.239**
16 Bahia	NE	**0.073**	**0.520**	**0.019**	**0.256**
17 MinasG	SE	**0.108**	0.301	**0.014**	0.133
18 EspSanto	SE	**0.019**	0.324	0.003	0.144
19 RioJaneiro	SE	**0.095**	0.202	0.009	0.095
20 SaoPaulo	SE	**0.229**	0.166	**0.019**	0.083
21 Parana	S	0.059	0.237	0.006	0.100
22 StaCatari	S	0.034	0.136	0.002	0.055
23 RGSul	S	0.067	0.179	0.005	0.073
24 MtGrSul	CW	0.013	0.289	0.002	0.120
25 MtGrosso	CW	0.015	0.251	0.002	0.106
26 Goias	CW	0.031	0.300	0.004	0.126
27 DF	CW	0.013	0.219	0.001	0.106
Total	Brazil	1.000	0.308	0.145	0.145

*Macro-Regions: N = North; NE = North-East; SE = South-East; S = South; CW = Center-West

[15] The poverty gap and poverty line values are constructed with "adult equivalent" per capita household income.

The last column in the table above shows the regional insufficiency gap. The picture is similar to what was seen for the number of households below the poverty line, with the states in the NE regions plus the states of Tocantins and Para showing the highest poverty gaps. Two states in the South region (Santa Catarina and Rio Grande do Sul) show the lowest poverty gaps in Brazil, followed closely by São Paulo. Interesting enough, Amapa state (in the North region) shows a poverty gap in line with the richer states of the S-SE. This result, however, should be viewed with caution, since that state has a very small share of total population, which could cause the result to be a sampling bias.

More information about the labor structure of the economy can be seen in the Tables 3 and 4. In these tables sectoral wage bills are split into the model's 10 occupational groups. The occupational groups are defined in terms of a unit wage ranking. More skilled workers, then, would be those in the highest income classes, and vice-versa. As can be seen in Table 3, Agriculture is the activity that uses more unskilled labor (40.5% of that sector's labor bill), while Petroleum and Gas Extraction and Petroleum Refinery are the most intensive skilled labor (10^{th} labor class) using activities, with Financial Institutions coming next. If labour inputs were measured in hours (rather than in values) the concentration of low-skill labour in Agriculture would be even more pronounced.

Agriculture is also the sector that hires the highest share of unskilled labor in Brazil, around 41% of total workers in income class 1. The Trade sector is the second largest employer of this type of labor. As for the higher income classes, we see that the Financial Institutions and Public Administration sectors hire the largest numbers of well-paid workers.

Table 4. Share (%) of occupations in each activity's labor bill.

	OCCUPATIONS (WAGE CLASS)										
Sectors	1	2	3	4	5	6	7	8	9	10	Total
Agriculture	40.5	30.2	5.8	6.0	5.2	3.3	3.7	1.8	1.9	1.6	100
MineralExtr	12.0	19.4	6.8	6.9	8.4	6.1	12.8	9.9	10.8	6.9	100
PetrGasExtr	0.0	0.0	0.0	0.9	0.9	6.1	16.1	12.1	22.8	41.1	100
MinNonMet	7.1	18.8	7.4	8.9	11.5	11.8	14.1	7.6	7.4	5.3	100
IronProduc	1.9	6.8	4.0	6.3	10.2	9.7	22.7	14.0	15.4	9.1	100
MetalNonFerr	1.9	6.8	4.0	6.3	10.2	9.7	22.7	14.0	15.4	9.1	100
OtherMetal	1.9	6.8	4.0	6.3	10.2	9.7	22.7	14.0	15.4	9.1	100
MachTractor	0.5	4.6	1.9	4.8	6.8	9.0	19.6	17.2	16.8	18.8	100
EletricMat	0.4	3.8	2.6	3.3	10.3	11.6	20.4	15.5	17.0	15.1	100
EletronEquip	0.4	3.8	2.6	3.3	10.3	11.6	20.4	15.5	17.0	15.1	100
Automobiles	0.3	2.5	1.0	2.4	7.7	8.6	19.6	15.7	22.4	19.8	100
OthVeicSpare	0.3	2.5	1.0	2.4	7.7	8.6	19.6	15.7	22.4	19.8	100
WoodFurnit	8.2	11.7	6.6	8.8	12.4	11.9	16.6	9.3	9.6	5.0	100
PaperGraph	2.3	7.8	3.7	6.2	8.4	8.1	18.7	13.0	16.7	15.1	100
RubberInd	0.8	4.7	3.2	4.6	14.4	5.5	24.0	13.6	16.6	12.5	100
ChemicElem	2.1	7.8	3.0	4.2	9.1	11.8	14.2	15.6	16.4	15.8	100
PetrolRefin	0.5	1.5	2.7	0.3	9.0	5.7	13.1	7.2	10.5	49.5	100
VariousChem	0.0	6.8	9.6	13.4	25.3	0.0	14.5	2.8	7.9	19.7	100
PharmacPerf	1.7	5.7	3.1	6.8	4.1	7.5	13.5	11.3	18.7	27.4	100
Plastics	1.6	6.3	2.3	8.5	12.8	12.1	24.6	10.3	9.0	12.6	100
Textiles	14.7	9.0	4.9	7.2	12.5	11.0	17.6	11.3	6.2	5.5	100
Apparel	3.2	17.3	7.5	15.1	16.1	9.7	15.7	5.4	4.5	5.5	100
ShoesInd	4.1	16.2	6.5	13.5	18.2	13.0	14.4	5.7	4.8	3.6	100
CoffeeInd	8.6	14.3	6.1	9.6	13.2	11.3	15.1	8.3	7.4	6.0	100
VegetProcess	8.6	14.3	6.1	9.6	13.2	11.3	15.1	8.3	7.4	6.0	100
Slaughter	8.6	14.3	6.1	9.6	13.2	11.3	15.1	8.3	7.4	6.0	100
Dairy	8.6	14.3	6.1	9.6	13.2	11.3	15.1	8.3	7.4	6.0	100
SugarInd	8.6	14.3	6.1	9.6	13.2	11.3	15.1	8.3	7.4	6.0	100
VegetOils	8.6	14.3	6.1	9.6	13.2	11.3	15.1	8.3	7.4	6.0	100
OthFood	8.6	14.3	6.1	9.6	13.2	11.3	15.1	8.3	7.4	6.0	100
VariousInd	16.8	13.4	6.6	6.2	11.4	7.4	13.1	7.8	10.7	6.5	100
PubUtilServ	1.7	17.5	5.3	8.6	7.1	6.0	12.9	12.2	14.2	14.5	100
CivilConst	6.3	13.4	8.6	10.1	12.5	9.0	20.2	9.6	6.9	3.4	100
Trade	10.0	14.2	6.6	8.2	10.7	8.2	15.1	8.3	10.0	8.7	100
Transport	4.6	7.0	4.4	4.7	7.5	7.1	19.0	16.1	18.1	11.6	100
Comunic	1.4	4.6	2.4	5.1	7.9	9.4	18.6	13.9	17.2	19.4	100
FinancInst	0.9	3.5	1.3	3.5	6.6	4.2	10.0	11.8	23.3	34.9	100
FamServic	16.4	20.3	7.4	8.4	9.6	6.8	12.1	6.5	7.2	5.4	100
EnterpServ	2.9	8.1	4.3	5.7	8.1	6.4	13.0	8.6	15.7	27.2	100
BuildRentals	2.0	4.3	2.7	4.8	9.9	6.3	17.1	8.8	18.4	25.7	100
PublAdm	1.7	13.1	3.6	7.2	7.6	6.8	13.0	12.1	19.3	15.6	100
NMercPriSer	7.6	16.6	6.0	9.2	9.3	10.9	13.7	8.2	11.6	6.9	100

Table 5. Share of each activity in total labor bill, by occupation.

	OCCUPATIONS (WAGE CLASS)									
Sectors	1	2	3	4	5	6	7	8	9	10
Agriculture	41.0	17.8	9.8	6.9	4.8	3.8	2.2	1.4	1.1	0.9
MineralExtr	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.2	0.1
PetrGasExtr	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.2	0.3	0.5
MinNonMet	0.5	0.8	0.9	0.8	0.8	1.0	0.6	0.5	0.3	0.2
IronProduc	0.1	0.1	0.2	0.2	0.3	0.3	0.4	0.3	0.3	0.2
MetalNonFerr	0.0	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.1	0.1
OtherMetal	0.3	0.7	1.2	1.3	1.7	1.9	2.4	2.0	1.5	0.9
MachTractor	0.1	0.5	0.5	0.9	1.1	1.7	2.0	2.3	1.6	1.8
EletricMat	0.0	0.1	0.2	0.2	0.5	0.7	0.7	0.7	0.5	0.5
EletronEquip	0.0	0.1	0.2	0.2	0.4	0.6	0.5	0.5	0.4	0.4
Automobiles	0.0	0.1	0.1	0.1	0.3	0.4	0.5	0.5	0.5	0.5
OthVeicSpare	0.0	0.2	0.2	0.3	0.8	1.1	1.3	1.3	1.4	1.2
WoodFurnit	0.9	0.7	1.1	1.0	1.2	1.4	1.0	0.8	0.6	0.3
PaperGraph	0.3	0.6	0.8	0.9	1.0	1.2	1.4	1.3	1.2	1.1
RubberInd	0.0	0.1	0.1	0.1	0.3	0.1	0.3	0.2	0.2	0.1
ChemicElem	0.1	0.1	0.2	0.1	0.3	0.4	0.3	0.4	0.3	0.3
PetrolRefin	0.0	0.1	0.3	0.0	0.5	0.4	0.5	0.3	0.4	1.7
VariousChem	0.0	0.3	1.1	1.0	1.6	0.0	0.6	0.2	0.3	0.8
PharmacPerf	0.1	0.2	0.3	0.4	0.2	0.5	0.5	0.5	0.6	0.9
Plastics	0.1	0.2	0.2	0.5	0.6	0.7	0.8	0.4	0.3	0.4
Textiles	0.7	0.2	0.4	0.4	0.5	0.6	0.5	0.4	0.2	0.1
Apparel	0.3	0.9	1.1	1.5	1.3	1.0	0.8	0.4	0.2	0.3
ShoesInd	0.2	0.4	0.4	0.6	0.7	0.6	0.3	0.2	0.1	0.1
CoffeeInd	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
VegetProcess	0.5	0.4	0.5	0.6	0.6	0.7	0.5	0.3	0.2	0.2
Slaughter	0.4	0.3	0.4	0.5	0.5	0.5	0.4	0.3	0.2	0.1
Dairy	0.1	0.1	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.0
SugarInd	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1
VegetOils	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
OthFood	1.0	1.0	1.2	1.2	1.4	1.5	1.0	0.7	0.5	0.4
VariousInd	0.7	0.3	0.5	0.3	0.5	0.4	0.3	0.3	0.3	0.2
PubUtilServ	0.5	3.2	2.8	3.0	2.0	2.1	2.4	3.0	2.5	2.6
CivilConst	2.7	3.3	6.1	4.8	4.9	4.3	5.0	3.2	1.6	0.8
Trade	13.5	11.2	14.8	12.6	13.3	12.5	12.0	8.7	7.5	6.6
Transport	2.6	2.3	4.1	3.0	3.8	4.4	6.2	7.0	5.6	3.6
Comunic	0.2	0.4	0.6	0.8	1.0	1.5	1.6	1.6	1.4	1.6
FinancInst	1.0	2.3	2.4	4.4	6.9	5.3	6.7	10.5	14.6	22.3
FamServic	21.0	15.1	15.8	12.1	11.2	9.8	9.0	6.5	5.1	3.9
EnterpServ	1.6	2.6	4.0	3.6	4.1	4.0	4.2	3.8	4.8	8.5
BuildRentals	0.1	0.2	0.3	0.3	0.6	0.4	0.6	0.4	0.6	0.9
PublAdm	6.4	29.4	23.3	31.2	26.7	29.3	29.2	36.3	40.8	33.7
NMercPriSer	2.2	2.8	2.9	3.0	2.4	3.5	2.3	1.8	1.8	1.1
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

And, finally, Table 6 shows the distribution of occupation wages (OCC) classes among the household income classes (POF classes).

Table 6. Wage bill distribution according to occupational wages and household income classes. 1996 million Reais.

Household Income Classes	OCCUPATIONAL WAGES CLASSES (personal)										
	OCC1	OCC2	OCC3	OCC4	OCC5	OCC6	OCC7	OCC8	OCC9	OCC10	Total
POF[1]	1531	1637	0	0	0	0	0	0	0	0	3168
POF[2]	538	2409	1632	783	0	0	0	0	0	0	5362
POF[3]	1804	3996	1201	2460	4327	3728	342	0	0	0	17859
POF[4]	766	1513	861	1380	1077	616	5020	0	0	0	11233
POF[5]	932	2787	1147	1649	2746	2254	5945	3526	0	0	20985
POF[6]	537	1811	795	1410	2133	2127	4305	5517	405	0	19039
POF[7]	576	2315	1178	2012	3038	3102	8717	7654	12773	0	41365
POF[8]	201	1137	524	1045	1819	1969	4896	5585	13211	1427	31814
POF[9]	123	695	401	762	1312	1449	4571	5218	15864	16994	47388
POF[10]	83	527	301	576	1135	1185	3939	5086	18480	134499	165811
Total	7091	18827	8040	12077	17586	16430	37734	32586	60732	152920	364024

In the table above the rows show household income classes, while the columns show the wages by occupation. It is evident from this table that the wage earnings of the higher wage occupations (OCC10, for example) are concentrated in the higher income households, and *vice-versa*. Most of the wages earned by workers in the first wage class (OCC1) accrue to the three poorest households, POF[1]-[3]. All the workers in the highest wage class, on the other hand, are located in households from the 8th income class and above.

5 The simulation

We will simulate the effects of a trade liberalization shock in the context of the Free Trade Area of Americas (FTAA) formation. As there is no probable detailed scenario arising so far from the negotiating process, we will use here a hypothetical 100% cut in all tariffs in trade between Brazil and its trade partners in the block. The shocks to be applied draw on previous work of the authors (Ferreira Filho, 2002), and are generated by tariff changes and prices adjustments results from a previous run of the GTAP[16] model with a linked (embedded) detailed Brazilian model, using a methodology described in Horridge and Ferreira Filho (2002).

The shocks to be transmitted to the PAID-BR (Poverty Analysis and Income Distribution Brazilian Model) are the Brazilian export quantities, the CIF import prices and the import tariff shocks to Brazil arising from the tariff liberalization shocks in the global model.

5.1 *Model closure*

It is worth stressing some points about the model closure. First, the shocks are generated from a previous GTAP model run, where the FTAA formation was simulated. Taking this into account, we tried to use in our model a closure as close as possible to the standard GTAP closure, with the RORDELTA = 0 option fixing the share of each region in total investment flow.

As for the labor market closure, there are many different possible choices. In this paper we have chosen to hold real wages fixed, with employment adjusting in each industry. With fixed wage relativities, the share of each occupation in each industry is also fixed; meaning that each activity will hire fixed proportions of the 10 model occupations.

In the capital market the capital stock in each sector is held fixed, with rates of return to capital adjusting endogenously. This closure has a short run flavour in the sense that capital stock is fixed in the short run. The ratio investment/consumption is also fixed. The trade balance is fixed, with real consumption, investment and government spending moving together to accommodate it. The trade balance, then, drives the level of these three last aggregates. And, finally, the consumer price index is the model's numeraire.

6 Results

6.1 *The CGE model results*

The Brazilian economy is little oriented to external trade. The shares of exports and imports in total GDP were respectively 7% and 8.9% in the 1996 base year. These shares have increased recently, but not by enough to significantly change this picture. Table 6 shows more information about the nature and size of the shocks applied to the model, as well as about the structure of Brazilian external trade. The final column shows simulated changes in output.

As stated before, the shocks applied to the model were generated by a previous run of the GTAP model. The GTAP effects on the Brazilian economy were then transmitted to the PAID-BR model through the following channels: export quantities, foreign currency import prices, and the aggregated (over regions in the global model) trade weighted import tariffs calculated in the GTAP model, version 5 database.

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[16] The GTAP version 5.0 database was used for this run.

Table 7. Shocks to the CGE model, 1996 external trade structure, and output results.

	SHOCKS			EXTERNAL TRADE				RESULT
	Import tariffs	Export quantities	Foreign currency import prices	Share in total Brazilian exports	Exported share of total output*	Import share in local markets	Share in total imports	% Change output
Coffee	-2.49	3.48	0.21	0	0	0	0.000	10.41
SugarCane	-0.82	-4.64	-0.11	0	0	0	0.000	0.18
PaddyRice	-0.3	-1.7	-0.27	0	0	0.02	0.001	0.18
Wheat	-1.18	3.64	-0.21	0	0	0.68	0.020	-1.42
Soybean	-5.48	4.41	1.2	0.019	0.17	0.06	0.004	-0.57
Cotton	-1.42	1.25	-0.21	0	0	0.02	0.000	-0.16
Corn	-1.27	-2.5	0.1	0.001	0.015	0.01	0.001	0.27
Livestock	-1.42	7.25	1.11	0	0	0.01	0.001	0.19
NaturMilk	-4.76	-2.23	-0.25	0	0	0	0.000	0.04
Poultry	-1.61	-5.68	-0.22	0	0.002	0.01	0.000	0.18
OtherAgric	-2.49	1.63	0.21	0.022	0.019	0.02	0.015	0.24
MineralExtr	-1.34	-4.16	0.54	0.059	0.398	0.09	0.006	-2.08
PetrGasExtr	-0.75	-3.67	0.46	0	0.002	0.41	0.063	-0.34
MinNonMet	-3.49	9.22	-0.04	0.014	0.033	0.04	0.009	0.42
IronProduc	-2.45	3.68	-0.27	0.073	0.154	0.03	0.009	0.49
MetalNonFerr	-4.96	0.68	0.59	0.041	0.196	0.1	0.014	-1.31
OtherMetal	-3.19	2.52	-0.21	0.018	0.037	0.06	0.018	-0.01
MachTractor	-0.84	37.95	0.1	0.038	0.077	0.22	0.088	0.34
EletricMat	-3.92	0.00	-0.2	0.027	0.086	0.19	0.040	-1.86
EletronEquip	-6.53	10.23	0.00	0.018	0.047	0.36	0.123	-1.35
Automobiles	-4.6	-9.42	-1.07	0.029	0.057	0.1	0.034	-2.29
OthVeicSpare	-0.84	37.85	0.1	0.068	0.144	0.2	0.057	4.55
WoodFurnit	-5.24	-2.68	-0.1	0.026	0.078	0.02	0.004	0.19
PaperGraph	-3.93	-2.9	-0.04	0.032	0.067	0.06	0.018	-0.25
RubberInd	-3.35	2.35	-0.14	0.012	0.071	0.1	0.010	-0.12
ChemicElem	-3.35	1.99	-0.14	0.016	0.066	0.15	0.032	-0.60
PetrolRefin	-2.16	-0.01	-0.09	0.031	0.034	0.11	0.083	-0.32
VariousChem	-3.35	2.41	-0.14	0.015	0.039	0.1	0.028	-0.30
PharmacPerf	-3.35	2.32	-0.14	0.007	0.021	0.15	0.028	0.47
Plastics	-3.35	2.05	-0.14	0.004	0.021	0.07	0.010	0.14
Textiles	-3.09	8.58	-0.36	0.02	0.052	0.11	0.031	-0.19
Apparel	-2.42	9.87	-0.38	0.003	0.011	0.03	0.005	0.48
ShoesInd	-0.58	35.7	-0.72	0.043	0.294	0.1	0.006	14.14
CoffeeInd	-4.15	43.2	-0.33	0.033	0.237	0	0.000	16.01
VegetProcess	-2.77	4.26	-0.66	0.058	0.105	0.04	0.012	0.29
Slaughter	-1.79	-4.48	-0.45	0.025	0.055	0.02	0.004	0.15
Dairy	-0.86	11.39	-0.69	0.001	0.003	0.05	0.007	-0.20
SugarInd	-1.66	3.55	-0.3	0.029	0.217	0	0.000	1.21
VegetOils	-3.53	-1.52	-0.67	0.065	0.229	0.04	0.006	-0.69
OthFood	-2.77	4.32	-0.66	0.022	0.029	0.05	0.020	0.09
VariousInd	-3.76	7.37	-0.16	0.01	0.049	0.22	0.028	-1.16
PubUtilServ	0.00	-5.03	0.13	0	0	0.03	0.014	0.60
CivilConst	0.00	-2.74	-0.16	0	0	0	0.000	0.95
Trade	0.00	-5.79	-0.17	0.009	0.016	0.01	0.011	0.88
Transport	0.00	-4.5	-0.03	0.053	0.084	0.04	0.022	0.19
Comunic	0.00	-3.48	-0.05	0.005	0.014	0.01	0.003	0.58
FinancInst	0.00	-5.56	-0.03	0.007	0.006	0.01	0.006	0.44
FamServic	0.00	-5.38	-0.13	0.016	0.01	0.05	0.067	0.87
EnterpServ	0.00	-5.87	0.14	0.019	0.027	0.05	0.029	0.13
BuildRentals	0.00	0.92	0.47	0	0	0	0.000	0.04
PublAdm	0.00	-5.78	0.13	0.01	0.003	0.01	0.012	0.92
NMercPriSer	0.00	-3.3	-0.13	0	0	0	0.000	1.06

*- Calculated over FOB prices.

An inspection of Table 6 can give an idea of the importance of these shocks combined with the importance of each commodity in Brazilian external trade. As can be seen, Brazilian exports are spread among many different commodities, with no specialized trend. Imports as a share of each commodity domestic production are concentrated in Wheat, Oil, Machinery, Electric Materials and Electronic Equipment, and Chemical Products. In terms of total imports shares, however, Oil Products (Raw and Refined), Machinery, Electric Materials and Electronic Equipment, and Chemical Products are the most important products.

The changes in the foreign currency import prices in the model are generated by the world price adjustments in the global model. From the export side, we see that there is an export push arising from the trade liberalization in some of the Brazilian main export products: Iron Products, Machinery and Tractors, Other Vehicles and Spare Parts, and Processed Vegetable Products (VegetProcess), to cite the most import products in terms of exported share in the base year. On the other hand exports of Minerals and Vegetable Oils[17]contract. From the import side there is a general fall in import tariffs, only partially counteracted by higher world prices.

In what follows, we present some macro results in order to establish a benchmark for the regional and poverty analysis. When interpreting these results one should bear in mind that the model has a “top-down” inter-regional specification, meaning that the national model is solved before the inter-regional one, being exogenous to it.

The first observed result of our simulation is an increase in activity level in the model, as a result of trade liberalization. The increase in exports, consumption, government consumption and investment (which follow household consumption by means of the closure) outweigh the increase in imports, causing GDP to rise by 0.68%. The real exchange rate rises, with corresponding gains in the external terms of trade.

For factor market results, recall that sectoral capital and land are fixed, while employment adjusts to accomodate fixed real wages. As we can see, the average (aggregated) capital rental shows a 1.61% increase. With capital stocks fixed, output increases require employment increases (1.06% overall); so falling capital/labour ratios increase the marginal productivity of capital and hence capital returns. The price of land also shows a strong increase, reflecting the increase in production of activities using this factor (Agriculture).

Aggregate employment measured using wage bill weights rose by 1.06%, but rose more in terms of hours worked (PNAD head weights): 1.5%. This means that not only did

[17] This effect was discussed in more detail in Ferreira Filho (2002).

employment rise, but employment patterns also shifted towards the sectors where low-wage workers were employed -- boding well for a more equal income distribution.

Table 8. Selected macroeconomic results.

Macros	% changes
Imports price index, C.I.F., local currency	-3.10
GDP price index, expenditure side	0.33
Duty-paid imports price index, local currency	-5.57
Real devaluation	-3.42
Terms of trade	3.65
Average capital rental	1.61
Average land rental	5.69
Aggregate investment price index	0.03
Average capital rental	1.61
Consumer price index	Numeraire
Exports price index, local currency	0.44
Government price index	-0.12
Utility per household	1.81
Import volume index, C.I.F. weights	9.66
Real GDP	0.68
Aggregate employment, wage bill weights	1.06
Aggregate employment, PNAD head weights	1.50
Import volume index, duty-paid weights	9.64
Real household consumption	0.99
Export volume index	7.24

Table 9 shows results at regional level. With real wages fixed and the CPI acting as a numeraire, each region’s wage bills will change in proportion to (wage-weighted) regional employment. The change in aggregate labor demand will be distributed among regions according to their activity level changes. As can be seen in Table 9, some of the more populous states in Brazil (Sao Paulo, Rio de Janeiro and Bahia) a smaller increase in regional employment. Espirito Santo state, on the other hand, is the one where employment increases the most, a result due to an increase in the production of one commodity (coffee) that is very important for the local economy. But this is a small state compared with the above-mentioned.

Table 9. Regional results, 27 regions. % changes, Brazil.

REGIONS	Regional aggregate employment	Activity level	Regional aggregate consumption
Rondonia	1.37	1.03	1.17
Acre	1.08	0.72	0.91
Amazonas	0.76	0.41	0.59
Roraima	1.01	0.65	0.84
Para	0.81	0.42	0.64
Amapa	0.85	0.59	0.69
Tocantins	1.17	0.53	0.99
Maranhao	0.83	0.36	0.66
Piaui	1.09	0.67	0.99
Ceara	1.21	0.70	1.07
RGNorte	1.07	0.63	0.93
Paraiba	1.64	1.08	1.47
Pernambuco	1.09	0.59	0.94
Alagoas	0.99	0.56	0.86
Sergipe	1.38	0.93	1.22
Bahia	0.88	0.42	0.79
MinasG	1.30	0.88	1.25
EspSanto	2.25	2.07	2.23
RioJaneiro	0.84	0.37	0.71
SaoPaulo	0.97	0.50	0.88
Parana	1.25	0.71	1.19
StaCatari	0.89	0.40	0.83
RGSul	1.52	0.90	1.48
MtGrSul	0.92	0.38	0.86
MtGrosso	0.77	0.27	0.70
Goias	1.07	0.50	1.01
DF	1.00	0.64	0.94

6.2 *Poverty and income distribution results*

We saw in the previous section that model results are differentiated among regions, and among different household income classes. The results of these changes upon the poverty and income inequality measures are discussed below. Table 10 shows some aggregated figures, for the two different updating methods described earlier. We note that the GINI index fell by 0.14% in the first MS method (M1) and by 0.32% in the second method (M2).

It can also be seen from the table the effects of the two different updating methods we used. Method 2 (M2) does the relocation of the jobs to unemployed workers, for occupations and regions where employment rises. Method 2 tends to relocate jobs to the lower groups where unemployment rates are highest. That’s why the largest difference in income change occurs in the first POF income group. As seen before, this is the income stratum where most of the unemployed are located. Indeed, the last column shows a 4.6 percent fall in the aggregate rate of unemployment for this income class in the simulation. For the higher strata, on the other hand, Method 2 predicts a slightly smaller income rise than Method 1.

Table 10. Average household income and GINI index change, two updating methods.

	Average income (% variation)		(% points change)
	UPDATING METHOD		Unemployment rate
Household income group	M1	M2	M2
POF[1]	1.3	21.0	-4.6
POF[2]	1.4	3.3	-2.3
POF[3]	1.6	2.0	-1.4
POF[4]	1.6	1.6	-1.2
POF[5]	1.5	1.3	-1.0
POF[6]	1.6	1.1	-1.0
POF[7]	1.4	1.2	-0.9
POF[8]	1.3	0.8	-0.8
POF[9]	1.2	1.1	-0.9
POF[10]	1.0	0.8	-0.7
GINI INDEX	-0.14	-0.32	---

Note that in our model there is no substitution among workers in different wage classes, which we use as a proxy for skills. The fall in unemployment is a compositional effect arising from the uneven change in economic activity among different regions and sectors. These results show, then, that the integration scenario we simulate would be more beneficial, in terms of reduced unemployment, for the poorest households.

In what follows, we will stick only to the presentation of results due to the second updating method, the "quantum" method, for simplicity. The next table summarizes the results for each household contribution to the FGT indexes (compare with Table 2).

Table 11. Decomposition of the Foster-Greer-Thorbeck index according to household income class contributions.

Household income class	Contribution to FGT0	Contribution to FGT1	Contribution to FGT2
POF[1]	-0.0023	-0.0034	-0.0036
POF[2]	-0.0012	-0.0008	-0.0005
POF[3]	-0.0016	-0.0006	-0.0002
POF[4]	-0.0006	-0.0001	0.0000
POF[5]	-0.0004	0.0000	0.0000
POF[6]	-0.0001	0.0000	0.0000
POF[7]	0.0000	0.0000	0.0000
POF[8]	0.0000	0.0000	0.0000
POF[9]	0.0000	0.0000	0.0000
POF[10]	0.0000	0.0000	0.0000
Total	-0.0061	-0.0049	-0.0042
Original Values	0.3079	0.1449	0.0960

FGT0- proportion of poor households, or headcount ratio; FGT1- average poverty gap; FGT2-extent of inequality among the poor.

We can see from the table that the three inequality measures are slightly reduced, with again the reductions concentrating in the poorest households: the proportion of poor households, the poverty gap and the extent of inequality all fall in the poorest households. The fall in the number of poor, amounts to a 1.99% fall in aggregate poverty if the calculation is performed over households, and 1.77% if over persons.

Table 12. Number and % change of regional households/persons who leave poverty.

Regions	Number of poor households	% change	Number of poor persons	% change	% change employment (heads)
1 Rondonia	-1562	-1.77	-5816	-1.70	1.66
2 Acre	-472	-1.25	-1699	-1.08	1.33
3 Amazonas	-2520	-1.12	-11317	-1.15	0.87
4 Roraima	-504	-2.16	-1631	-1.58	1.35
5 Para	-6295	-1.26	-23209	-1.14	1.14
6 Amapa	-341	-1.73	-1742	-1.83	1.03
7 Tocantins	-1563	-1.12	-5735	-1.00	1.28
8 Maranhao	-7763	-0.93	-29082	-0.79	1.05
9 Piaui	-2246	-0.51	-8435	-0.47	1.04
10 Ceara	-12490	-1.11	-44379	-0.97	1.52
11 RGNorte	-3868	-1.02	-15843	-1.07	1.18
12 Paraiba	-7384	-1.39	-26840	-1.25	1.68
13 Pernambuco	-10994	-0.95	-38069	-0.82	1.22
14 Alagoas	-2950	-0.67	-9438	-0.51	1.07
15 Sergipe	-2468	-0.94	-8046	-0.79	1.33
16 Bahia	-16539	-0.86	-59065	-0.76	1.30
17 MinasG	-43563	-2.65	-155709	-2.49	1.88
18 EspSanto	-15529	-5.08	-54390	-4.69	3.69
19 RioJaneiro	-18823	-1.96	-61346	-1.78	1.20
20 SaoPaulo	-66824	-3.50	-227387	-3.22	1.45
21 Parana	-18042	-2.58	-60858	-2.33	1.53
22 StaCatari	-6890	-3.00	-24349	-2.80	1.09
23 RGSul	-36348	-6.01	-121474	-5.49	2.37
24 MtGrSul	-4330	-2.31	-15172	-2.22	1.26
25 MtGrosso	-3855	-2.02	-14355	-1.93	1.08
26 Goias	-9533	-2.02	-35765	-2.06	1.28
27 DF	-3638	-2.64	-13474	-2.59	1.24
Total	-307333	---	-1074620	---	1.50

7 Concluding remarks

A series of points should be highlighted in wrapping up this discussion. As we could see, model results show that even an important shock as that applied here could be not enough to generate dramatic changes in the structure of the Brazilian economy. Even our strong liberalization experiment would have only a moderate effect on aggregate economic activity. The simulated effects on poverty and income distribution, although not negligible, do not seem to be extreme. This highlights two important aspects of this issue, one related to the structure of the Brazilian economy, and other to an aspect of poverty.

In terms of the Brazilian economy, it was shown that it is not very oriented towards external trade. The domestic market is far bigger and more important for the general economy than the external market, an aspect long understood by researchers. This makes it naturally less sensitive to tariff structure changes, as well as to changes in export demand.

But it should also be noted that approaching poverty by the household dimension, instead of by the personal dimension, and tracking the changes in the labor market from individual workers to households is an important modeling issue. To our best knowledge, this is maybe the first methodological approach that tracks employment by sector and region to household income via the incomes of individual family members. If spending (and welfare) is in any sense a household phenomenon, this is the appropriated method for doing so. Even though there may be a somewhat higher computational cost associated with this procedure, it seems worthwhile.

This research can be extended in a series of new directions. Maybe one of the more obvious would be to try to assess in a more direct way the importance of agricultural trade liberalization for poverty in Brazil. As we saw, the agricultural sector is one of the more important sectors in absorbing unskilled workers. Considering that agriculture is still one of the main sticking points in economic integration negotiations, this would be a natural extension for this analysis.

And, finally, it’s worth noting that our model does not assess dynamic effects, or effects upon productivity gains, usually thought to be important trade liberalization effects. We have in this paper assessed a more short-run effect, highlighting compositional and regional structure differences.

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9 APPENDIX 1

In this section we provide details of the construction of the microsimulation database and how we linked it to the CGE model.

9.1 *Processing the PNAD data*

We used SAS to perform preliminary processing of the PNAD dataset. A very few anomalous records were deleted. A text extract of the PNAD data was created containing selected data fields (shown below), and converted to a GEMPACK HAR file. GEMPACK was used for most subsequent processing. The HAR file contained attributes of 263938 adults grouped into 112055 households. No attributes of children under 15 were retained.

The attributes of each household were:

REGION	one of the 27 Brazilian states,
NADULT	number of adults
NCHILD	number of children under 15
WEIGHT	sample weight (ranging from 144 to 857)

The sample weights vary according to the municipality where data was collected, and equal the ratio of actual households (in that municipality) to the number of interviewed households. Thus, multiplying each PNAD observation by the corresponding household weight gives estimates for the whole Brazilian population.

The attributes of each adult were:

HOU	which household they belong to
BOSS	1 if self-employed
SEX	1=male 0=female
RACE	White,Black,Other
LITERATE	0 or 1 (true)
ATSCHOOL	0 or 1 (true)
YRSSCHOOL	years of schooling arranged in 6 groups:
	YLT1,Y1_3,Y4_7,Y8_10,Y11_14,YGT14
FAMHEAD	0 or 1 (if head of the family)
EMPLOYED	0=Unemployed,1=hasjob,2=retired or not in LF
SECTOR	sector of employment (1 to 41)
MIGRANT	0 or 1 (born in another state)

AGE	one of 10 age brackets Y15to19, Y20to24,Y25to29, Y30to34, Y35to39, Y40to44, Y45to49, Y50to54, Y55to59, Y60plus
TRANSFERS	monthly transfer income (mainly pensions)
WAGE	monthly wage income
NONWAGE	monthly other income

Apart from the last 3 income variables all these attributes were categorial, ie, integer-valued.

A high WAGE measure might arise from high hourly wages or from long hours of work: price and quantity effects are combined. To help decompose these effects at a later stage of our computations we added a new real-valued attribute for each worker, JOBSCORE, to act as a a quantity measure. We initialized this to 1 for each employed worker, else 0.

Nearly 10% of those who stated they had a job, did not record a monthly wage. Most of these worked in agriculture. The explanation may be that they worked as part of a family team (but received no individual wages), or that they received no wages in the survey month for some other reason (seasonal lay-off, sick).

We imputed wages to these wageless workers by using the results of a multiple regression. The natural log of positive monthly wages was regressed against a vector of binary dummy variables constructed from the attributes listed above. Then, we predicted a wage for the wageless workers using their attributes and the regression results. Since the regression results are of some interest in themselves, they are listed overleaf. They show, for instance, that being male increases the wage by 50% (=exp(0.4)-1), or that tertiary education tends to double the wage (exp(1.529-0.760)-1). In forming dummies for multivalued variables, the first value was dropped. Hence, for example, regional wage effects are shown relative to region 1, Rondonia.

Results of Wage Regression

BETABIN	Estimate	t_value
Constant	3.864	133.99
BOSS	0.800	90.55
SEX	0.400	87.65
LITERATE	0.234	22.81
ATSCHOOL	0.004	0.62
FAMHEAD	0.192	42.89
MIGRANT	0.036	8.96

BETASKOOL	Estimate	t_value
YLT1		
Y1_3	0.021	2.13
Y4_7	0.199	19.46
Y8_10	0.416	38.72
Y11_14	0.760	71.47
YGT14	1.529	126.19

BETAAGE	Estimate	t_value
Y15to19		
Y20to24	0.373	32.10
Y25to29	0.580	48.91
Y30to34	0.694	57.43
Y35to39	0.770	63.06
Y40to44	0.819	66.18
Y45to49	0.852	67.19
Y50to54	0.870	66.13
Y55to59	0.834	59.61
Y60plus	0.684	50.15

R-squared	0.54874
SSt	144514
SSe	79300
SSr	65213
Nobs	142962
Npar	89

BETASEC	Estimate	t_value
cafe		
cana	0.294	9.47
arroz	-0.238	-7.48
trigo	0.695	3.07
soja	0.480	12.90
algod	-0.327	-4.46
milho	-0.465	-17.64
pecuar	0.185	8.28
aves	-0.105	-2.42
outagr	-0.078	-3.59
Mineral	0.393	10.36
PetrGas	1.075	16.59
MinNonM	0.384	13.83
SidMetO	0.492	19.37
MachTra	0.594	19.76
MatElEl	0.542	15.77
AutomPe	0.650	20.80
WoodFur	0.346	14.14
PaperGr	0.507	17.19
RubberI	0.520	7.88
ChemicE	0.605	16.46
PetrolR	0.997	14.32
vachem	0.427	3.58
Pharmac	0.700	15.71
Plastic	0.473	12.43
Textile	0.208	6.38
Apparel	0.472	17.57
ShoesIn	0.436	15.82
FoodInd	0.359	15.61
vaind	0.188	5.91
PubUtil	0.575	20.92
CivilCo	0.354	16.80
Trade	0.365	17.66
Transpo	0.595	27.31
Comunic	0.623	22.31
FinancI	0.792	30.90
FamServ	0.253	12.33
EnterpS	0.565	25.41
BuildRe	0.669	18.26
PublAdm	0.567	26.92
NMercPr	0.327	12.87

BETAREG	Estimate	t_value
Rondonia		
Acre	-0.026	-0.95
Amazonas	-0.058	-2.72
Roraima	0.118	3.65
Para	-0.160	-8.68
Amapa	0.184	5.52
Tocantins	-0.233	-10.55
Maranhao	-0.308	-14.14
Piaui	-0.631	-27.24
Ceara	-0.453	-25.11
RGNorte	-0.364	-16.16
Paraiba	-0.467	-21.46
Pernambuco	-0.336	-18.67
Alagoas	-0.343	-14.94
Sergipe	-0.289	-12.68
Bahia	-0.304	-17.34
MinasG	-0.144	-8.32
EspSanto	-0.142	-6.77
RioJaneiro	0.025	1.42
SaoPaulo	0.182	10.58
Parana	-0.044	-2.40
StaCatari	0.065	3.30
RGSul	-0.018	-1.04
MtGrSul	-0.092	-4.40
MtGrosso	0.112	5.49
Goias	-0.093	-5.09
DF	0.277	14.34

BETAETH	Estimate	t_value
White		
Black	-0.142	-18.3
Other	-0.130	-30.6

The above regression results were used to impute wages to wageless workers. Next, we scaled all wages by a common factor so that the wage total (taking into account the survey weights) was the same as total annual wages in the CGE model database (from the IO tables). The same factor was used to scale transfer and other non-wage income. After the scaling the two databases compared as follows:

CGE model		PNAD data	
Land	10088	Wage	364024
Labour	364008	Nonwage	16767
Capital	289661	Transfers	87849

Even allowing for the capital income that is sent overseas, it clear that the PNAD either under-reports capital income, or mis-labels capital income as wage income. We believed that this problem mainly affects the richer groups, so does not vitiate our poverty analysis. However, it illustrates the difficulty of fully reconciling the CGE and microsimulation databases.

In the simulation we allow workers to move between sectors, but not between regions or occupations. We divided all the workers into 10 occupational groups, based on their wages. Hence, in our model, economists (but not farm-workers) can become dentists. The workers were ranked by wage, and divided into 10 approximately equal-sized groups (some monthly wage levels, eg R250 per month, were very common, so wage brackets could not define exactly equal deciles). The numbers and bracket bounds are shown in the table below.

Workers Occupational Groups

Occ group	Monthly wage up to:	Employed (weighted)	Unemployed (weighted)	% Unemployed
OCC1	100	10828743	515515	4.5
OCC2	180	12567070	1860703	12.9
OCC3	200	4279506	452811	9.6
OCC4	250	5375141	1119502	17.2
OCC5	300	6387328	878474	12.1
OCC6	374	4977000	969927	16.3
OCC7	500	8944044	865095	8.8
OCC8	700	5558940	506612	8.4
OCC9	1200	6747603	249637	3.6
OCC10	-	5879128	82751	1.4
Total		71544501	7501027	9.5

Another, very similar, regression was used to predict the wages of unemployed persons (if they were to get a job). The PNAD did not record a sector of employment for these, so no sectoral dummies were used. The R-squared for this regression was 0.52. The predicted wage of each unemployed person was used to place that person in one of the 10 occupational groups.

The IO tables on which the CGE model data are based do not distinguish between labour types. We used the PNAD occupational share of national sectoral wage bills to divide each IO national sectoral wage bill between the 10 occupations. Thus the CGE model used the same 10 occupational categories and industry occupation shares as the microsimulation data.

9.2 *Household expenditure patterns and income groups from the POF survey*

The PNAD survey did not distinguish household expenditure patterns. We used another survey, the POF, covering 16,000 households in the metropolitan areas of 11 regions, to provide these data. The POF divides households into regions and into 10 family income groups. In the POF, income brackets are defined as multiples of the minimum wage: for example the 6th group, M8T10, receives from 8 to 10 times the minimum monthly wage. Instead of assigning to each PNAD household a single POF household (which would be difficult) we used the POF to define 110 expenditure bundles (11 regions times 10 POF income groups). The POF spending categories were mapped to the 52 commodities distinguished by the CGE model. Each PNAD household was assigned to one of these expenditure patterns. To do the assignment, we ranked all PNAD households according to household income. Each household was assigned to a POF group in accordance with its position in the ranking. For example (see below), since 11.7% of POF familes were in the poorest group, we assigned the poorest 11.7% of PNAD familes to the first POF income group.

POF family income groups

POF group	% of all families	Alternate group name	Estimated propensity to consume
POF[1] poorest	11.7	M0T2	1.00
POF[2]	9.3	M2T3	0.95
POF[3]	16.4	M3T5	0.80
POF[4]	7.1	M5T6	0.75
POF[5]	10.7	M6T8	0.73
POF[6]	7.5	M8T10	0.69
POF[7]	12.3	M10T15	0.65
POF[8]	7.0	M15T20	0.66
POF[9]	7.4	M20T30	0.60
POF[10] richest	10.6	M30	0.56
Total	100.0		

Each of the 27 states distinguished in the PNAD was mapped to one of the 11 POF zones (most of Amazonia is one POF zone). The POF also allowed us to estimate propensities to consume by POF group. We multiplies each PNAD household's income by one of these propensities to estimate its total spending, and divided this total spending among commodities to form an initial matrix showing household expenditure by 52 CGE model commodities, by 27 regions, and by 10 household income groups. Then this initial spending matrix was scaled so that total spending by commodity (ie, summed over regions and POF groups) was equal to the consumption vector in the CGE model dataset. The same Frisch parameters and expenditure elasticities were initially assigned to all households. Expenditure elasticities were then normalized so they averaged to 1 (budget shares differed by region and household income group).

In summary, we used the POF to divide PNAD families into 10 income groups, and to estimate consumption patterns by 10 income groups and 27 regions. Spending by these 270 representative consumers was made to add to national totals from the IO tables.

There is naturally a correlation between the 10 occupational groups and the 10 household types. Most of the wage income of the poorest households comes from the lower-paid occupations: see Table 5 in the main text.

9.3 *Income measures for poverty statistics*

We computed four well-known measures of poverty:

- the Gini index.
- the proportion of poor households (ie, below the poverty line), also known as Foster-Greer-Thorbecke 0 [FGT0].
- the average poverty gap (proportion by which poor households fall below the poverty line), aka FGT1.
- the squared poverty-gap index, aka FGT2, measures the extent of inequality among the poor.

In each case, our income measure was adjusted according to the number of persons in the household. We defined "equivalent income" as household income divided by a measure of spending need given by: 1 for the first adult, plus 0.75 for each other adult, plus 0.5 for each child. Thus a family of 2 adults and 2 children receiving R$1000 per month, would have an equivalent income of R$364 (=1000/(1+0.75+1)).

The poverty line used in the 3 Foster-Greer-Thorbecke indices was arbitrarily set at 1/3 of the average household equivalent income. In computing all 4 poverty indices, we took account of the PNAD survey weights.

The table below decomposes the 3 FGT indices to show how poverty is concentrated in the lower income groups, yet occurs also in the middle groups (because of the equivalence adjustment). For example, 3.9% of POF group 6 are poor -- they have a middle income but many dependents.

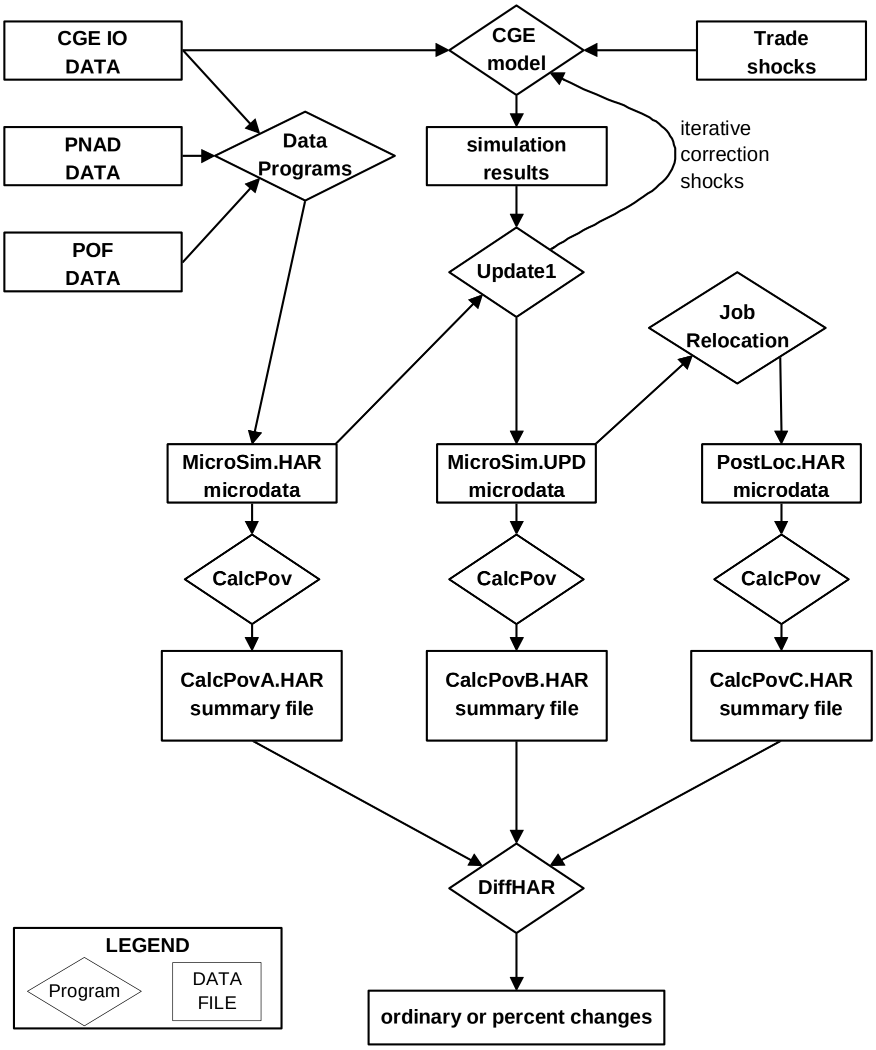
POF group contributions to FGT poverty indices

POF group	% of all families	share below poverty line	average poverty gap	contributions to FGT0	contributions to FGT1	contributions to FGT2
POF[1] poorest	10.7	0.9617	0.7334	0.1122	0.0856	0.0715
POF[2]	8.0	0.7657	0.3047	0.0716	0.0285	0.0135
POF[3]	16.0	0.5355	0.1496	0.0877	0.0245	0.0092
POF[4]	7.3	0.2837	0.0539	0.0202	0.0038	0.0011
POF[5]	11.0	0.1143	0.0189	0.0122	0.0020	0.0005
POF[6]	7.9	**0.0390**	0.0054	0.0029	0.0004	0.0001
POF[7]	12.9	0.0082	0.0009	0.0010	0.0001	0.0000
POF[8]	7.5	0.0008	0.0001	0.0001	0.0000	0.0000
POF[9]	7.7	0.0000	0.0000	0.0000	0.0000	0.0000
POF[10] richest	10.9	0.0000	0.0000	0.0000	0.0000	0.0000
	sum=100	FGT0= ave=0.3079	FGT1= ave=0.1449	FGT0= sum=0.3079	FGT1= sum=0.1449	FGT2= sum=0.0960

Slightly different results would have been obtained if we had computed the proportion of persons (rather than households) below the poverty line. Poorer households tend to contain more people, so the share of persons below the poverty line would be a little larger than the household shares we report. For example, the 30.8% of households that are below the poverty line account for 36% of individuals.

When computing poverty indices from updated microdata, we updated the poverty line by the change in the national CPI. In fact CPI movements differed according to POF group and region, but these differences are not reflected in our summary poverty measures.

9.4 *Linking CGE results to the micro level data*



Overview of data and simulation processes

The figure above shows the main steps in linking CGE and micro-simulation models. At top left, we see the process described above, of linking IO, PNAD, and POF data to create an initial or base microsimulation database. This database, MicroSim.HAR records the attributes of all the PNAD adults (including the houshold they belong to). The CalcPov GEMPACK program (at middle left) is used to compute poverty indices and many other summary statistics from this base data.

MicroSim.HAR also contains conventional matrix data (ie, not unit record) showing wage bills by 10 occupations, 27 regions, 10 POF groups and 41 PNAD sectors, non-wage income and transfers by 27 regions and 10 POF groups, and a matrix of household purchases by 27 regions, 10 POF groups, and 52 CGE model commodities. These matrices are a sufficiently detailed summary of the microdata to allow us to calibrate a conventional CGE model with 270 (27 regions x 10 POF groups) representative households which spend on 52 commodities and each draw income from 412 sources (41 sectors x 10 occupations + 2 non-wage sources -- we assume that all wage income generated in a region accrues to a household in that region).

At top right of the diagram we see the CGE model responding to an external shock and generating percentage changes in employment and wages for each of 10 occupations, 27 regions, and 41 PNAD sectors -- 1170 price and quantity changes.

The Update1 program (diagram centre) has two tasks:

- **A**: Update1 uses the 1170 labour price and quantity % changes to update each wage receipt in the microdata. Percent changes in labour prices are used to update the WAGE attribute, while percent changes in labour demand are used to update the hours-worked variable JOBSCORE. In other words, we assume at this stage that changes in labour demand are accomodated by existing workers working more or fewer hours. No-one is hired or fired. Transfer and other non-wage income received by each household are also updated -- they just follow national nominal GDP. The result is the updated microdata file MicroSim.UPD. Only the real valued JobScore, wage and income values are changed at this stage.
- **B**: Update1 computes changes in income of 270 representative households. These changes can be deduced either from the updated microdata or by updating the matrices (mentioned above) that summarize the microdata. Both methods give the same result -- under the assumption that no-one is hired or fired. The 270 income changes drive demands by each representative household for 52 commodities. A 270 x 52 LES demand system is modeled using conventional GEMPACK percent change variables and equations. In aggregate, these demand changes are not quite consistent with the aggregate household demands generated by the CGE model. We therefore feed back a small correction shock to the single national household of the CGE model to make it consistent with the 270 households. In principle, iteration might be required -- in practice one correction was enough.

We could very easily (and perhaps should) have embedded 270 households into the main CGE model, which would remove the need to feed back demand corrections, and leave only the simple task A for the Update1 procedure.

Our temporary assumption, that changes in labour demands are accommodated by existing workers working slightly more or less is computationally convenient. In a society like Brazil where under-employment is widespread it may even be partly realistic -- especially for the poorer groups, which are important to our poverty analysis. Results computed using this assumption are processed by the same CalcPov program used to summarize the original data.

The next stage of the computations instead makes the opposite assumption: that changes in labour demand occur by firing existing workers or by hiring the unemployed.

9.5 *Who gets hired? Who gets fired? They all do !*

Micro-simulation data is naturally discrete: some families have one child, some have 2 but none has 1.5 children. If the micro data survey contains 5000 workers in some occupation for which demand falls by 3%, then 150 must be fired. But which 150? Alternatively suppose that demand rose by 3%, creating 150 jobs. Which 150 of the 8000 unemployed in the microdata will get these jobs?

Several approaches have been suggested to this problem. For example, Savard (2003) constructs separate queues of employed and unemployed. The most hirable of the unemployed are the first to get jobs, whilst the least productive workers are fired first. Or, hirings and firing could be allocated randomly.

We pursue a different approach altogether, motivated by the following considerations:

- Our CGE model and microdata identify, in effect, 11070 separate firing problems (10 occupations, 27 regions, 41 PNAD sectors) since workers in each family are tagged with these attributes; and 270 hiring problems (since unemployed have no sector). It might be computationally expensive to construct 11340 separate queues.
- Perhaps 5000 of the 11070 different percent changes in employment will be negative. For example, employment by occupation 7 in region 3, sector 18 may fall by 5%. Perhaps in the survey data there are only 17 such workers. How do we choose 0.85 (=17*0.05) workers to fire?
- It is typical of CGE simulations that many changes, including many employment changes, are quite small: a subsidy to wheat might cause employment in the plastics sector to fall by 0.006%. This exacerbates the previous problem: we may have to allocate many small changes in employment which correspond to sub-unit changes in the microdata. Rounding to the nearest worker might bias results: we might include the larger employment rises in wheat whilst overlooking the small falls in other sectors. To avoid this we need a procedure for allocating 0.07 jobs in a particular sector and occupation.
- In our PNAD microdata, each observation has a weight, ranging from 150 to 850. We have to take these weights into account when computing totals. It will make a difference whether 1 new job is allocated to a household with weight 200 or with weight 600. This complicates the problem of distributing a discrete number of jobs.

Our procedure makes use of the survey weights to account for non-integer changes in employment, so avoiding the problems just listed.

9.5.1 **The method of quantum weights**

Quantum mechanics teaches that a particle does not have just one location and speed at a certain moment, but is better imagined as a 'probability cloud' showing the likelihood that the particle is in a certain position. Our fanciful adoption of the name reflects a feature of our job allocation process described below: instead of trying to decide whether or not a particular worker is fired, we modify our dataset to reflect both possibilities.

Suppose that in our updated survey data file MicroSim.UPD we have a household, with weight 200, containing only 1 worker and 3 children. We might represent this record as follows:

Weight 200	Region: Bahia	Children: 3	POF Group 3				
Adult 1	LF status: employed	wage: 200	JobScore: 0.95	Occupation 3	Sector: Apparel	Age: Y35to39	and so on

Above, the first row represents household attributes, with an additional row for each adult and and his/her attributes. We can see from the JobScore field that employment for workers of this type (Occupation,Sector,Region) has fallen by 5% (originally all JobScores were 1.0). In other words this worker is only working 95% of a normal job. We can restore the JobScore to an integer value by splitting the household into two records, thus:

Weight 190	Region: Bahia	Children: 3	POF Group 3				
Adult 1	LF status: employed	wage: 200	JobScore: 1	Occupation 3	Sector: Apparel	Age: Y35to39	and so on

and

Weight 10	Region: Bahia	Children: 3	POF Group 3				
Adult 1	LF status: unemployed	wage: -	JobScore: 0	Occupation 3	Sector: -	Age: Y35to39	and so on

Notice that the weights for the 2 new households sum to the original 200. The first household, with weight 190 (=95%*200), is otherwise identical to the original. The adult in the second household (weight 10=5%*200) is unemployed, and has no sector or wage. Although the second household has no income, we still label it as POF group 3; the POF group labels refer to initial household income group, and are not updated. Our programs are already equipped to deal with differing household weights (the PNAD requires this) so the only inconvenience of the split is that the number of records is increased.

Now suppose our household had two adults, both working in a sector/occupation/region that were declining (JobScore<1):

Weight 200	Region: Bahia	Children: 3	POF Group 3				
Adult 1	LF status: employed	wage: 300	JobScore: 0.95	Occupation 5	Sector: PubUtil	Age: Y35to39	and so on
Adult2	LF status: employed	wage: 200	JobScore: 0.90	Occupation 3	Sector: Apparel	Age: Y35to39	and so on

To account for Adult 1, 5% of the original record must be split off to create a record where Adult 1 has no job. To account for Adult 2, 10% of the original record must be split off to create a record where Adult 2 has no job. So we get 3 households:

Weight 170	Region: Bahia	Children: 3	POF Group 3				
Adult 1	LF status: employed	wage: 300	JobScore: 1	Occupation 5	Sector: PubUtil	Age: Y35to39	and so on
Adult2	LF status: employed	wage: 200	JobScore: 1	Occupation 3	Sector: Apparel	Age: Y30to34	and so on

original above; below the version where adult 1 loses the job

Weight 20	Region: Bahia	Children: 3	POF Group 3				
Adult 1	LF status: unemployed	wage: -	JobScore: 0	Occupation 5	Sector: -	Age: Y35to39	and so on
Adult2	LF status: employed	wage: 200	JobScore: 1	Occupation 3	Sector: Apparel	Age: Y30to34	and so on

and third, the version where adult 2 becomes unemployed

Weight 10	Region: Bahia	Children: 3	POF Group 3				
Adult 1	LF status: employed	wage: 300	JobScore: 1	Occupation 5	Sector: PubUtil	Age: Y35to39	and so on
Adult2	LF status: unemployed	wage: -	JobScore: 0	Occupation 3	Sector: -	Age: Y30to34	and so on

Notice that, taking the weights into account, the splitting preserves both the total employment and total earnings of the original record. However, the variance of family incomes is increased by the split. We could have created a 4th household where **both** adults lost their jobs -- with weight of 1 (=5%*10%*200) but most of the employment changes were too small to justify this step.

In general, we need to create a new household for each working adult with JobScore>1 and for each unemployed adult with an occupation in increasing demand. Since most households have either one or two adults in the labour force, and about half of the occ/sector/region labor demands fall, we need to approximately double the number of households. If we took into account unlucky cases such as the 4th household just mentioned the multiplication of household records could be more severe.

So far we have only examined cases where employment shrank. Suppose we had a record:

Weight 200	Region: Parana	Children: 4	POF Group 4				
Adult 1	LF status: employed	wage: 250	JobScore: 1.05	Occupation 3	Sector: FoodInd	Age: Y35to39	and so on

We would merely truncate the JobScore to convert this to:

Weight 200	Region: Parana	Children: 4	POF Group 4				
Adult 1	LF status: employed	wage: 250	JobScore: 1	Occupation 3	Sector: FoodInd	Age: Y35to39	and so on

No new record is created this time. The lost labour time (0.05*200) and lost wages (0.05*200*250) must be preserved (labelled by region and occupation) for later distribution to the unemployed.

Once we have processed all adults in a region we know how much labour and wages of each type must be distributed to unemployed. We also know how many unemployed there are of each type (recall, unemployed were assigned to an occupational group). We then pass through the records again, seeking to share out the jobs amongst the unemployed. Suppose we come upon a record:

Weight 150	Region: SaoPaulo	Children: 1	POF Group 4				
Adult 1	LF status: unemployed	wage: -	JobScore: 0	Occupation 3	Sector: -	Age: Y35to39	and so on

This adult represents 150 unemployed of occupation 3 in Sao Paulo. Suppose in total there were 30000 of such adults, so this adult is 0.5% of the total. If there are 20 jobs to distribute, the group represented by this adult should get 0.1 jobs. Therefore we split the record in proportions 149.9/0.1 to get two records:

Weight 149.9	Region: SaoPaulo	Children: 1	POF Group 4				
Adult 1	LF status: unemployed	wage: -	JobScore: 0	Occupation 3	Sector: -	Age: Y35to39	and so on

and the lucky ones:

Weight 0.1	Region: SaoPaulo	Children: 1	POF Group 4				
Adult 1	LF status: employed	wage: 356	JobScore: 1	Occupation 3	Sector: ?	Age: Y35to39	and so on

The wage can be worked out since we know how much income we took from over-worked persons of this occupation and region (principle of income conservation). This implies that new workers are assigned an average of the wages paid to this occupation *in expanding industries*. With wage given, the sector to which the worker is assigned does not affect income or poverty measures, so need not be known. In fact, we do assign sectors to the newly employed, using a random assignment from expanding sectors, with probabilities weighted according to size of sectoral employment increases for the relevant occupation and region.

We used a Pascal program to perform the above procedure. We note two potential problems:

- the number of new jobs created for a particular region and occupation might exceed the number of unemployed of that type. In the experiment described in this paper, the CGE model assumed labor of all types to be in elastic supply at a fixed real wage. Potentially the demand for new workers (from the CGE model) might exceed the supply (in the microdata). The problem occurred rarely in our simulations, mainly for higher-paid occupations in a few regions: recorded unemployment tends to be low amongst these groups. Since our focus was mainly on lower-paid workers, we were not very concerned. In Brazil there is no shortage of less-skilled labour. Our solution to the problem was to first mop up the unavailable unemployed, then to force workers in the bottleneck occupations to work a little harder (ie, we allowed a few JobScore values to remain above 1). Another solution would be to impose labour supply constraints in the CGE simulation.

- the second problem is subtle and rare (it occurred in 6 out of the 112055 original households). Suppose, for a particular region and occupation, that 2/3 of the unemployed are to get jobs. Suppose we have a household weight 300 with two such unemployed. According to the scheme outlined above we would create 2 new household records. The first, with weight 200 (=300*2/3) would allocate a job to Adult 1. The second new record, also with weight 200 would show Adult 2 as employed. Since the sum of weights must not change, the weight now assigned to the original household must be -100! Our solution was to assign a zero weight to the original household and weights of 100 to the 2 new households -- meaning that a few unemployed were denied the chance to work. Another solution, mentioned previously, would be to create a third new household in which both adults would get jobs.

Our job allocation procedure does not alter numbers employed or wages earned: it only redistributes jobs and income between adults of the same occupation and region. The effect on income distribution within such a group can be large, but the potential for disagreement with the CGE model results (as computed by Update1) is small, *as long as the job redistribution within occupations does not move income between the POF income groups which drive consumption*. In practice there is a strong correlation between occupational groups (based on individual earnings) and POF income groups (based on household earnings). Hence, job redistribution within occupations affects income distribution within, more than between, POF groups. We did not bother to feed back consumption changes, induced by the job reallocation, into the main CGE model.