Education or Inflation?

the Roles of Structural Factors and Macroeconomic Instability in Explaining Brazilian Inequality in the 1980s

by

Francisco H G Ferreira
The World Bank

and

Julie A Litchfield
STICERD, London School of Economics and Political Science

Discussion Paper
No. DARP 41
March 1999

The Toyota Centre
Suntory and Toyota International
Centres for Economics and
Related Disciplines
London School of Economics
Houghton Street
London WC2A 2AE
Tel.: 0202-7955 6678

We are grateful to the Leverhulme Trust, the CNPq in Brasilia, and STICERD for financial support; to Frank Cowell and Stephen Howes for invaluable guidance; to Rodolfo Hoffman and seminar participants at IPEA (Rio de Janeiro) for helpful comments; and to Kaspar Richter for excellent research assistance.

Abstract

This paper investigates possible explanations for the increases in inequality observed in Brazil during the 1980s. While the static decomposition of inequality by household characteristics reveal that education and race of the household head, as well as geographic locations, can account for a substantial proportion of inequality *levels*, a dynamic decomposition suggests that *changes* in inequality are not explained by income or allocation effects across these groupings, but by pure within-group inequality effects. The analysis then turns to the role of macroeconomic instability, and finds some significant correlation and regression coefficients which suggest a link between inflation and inequality, while poverty appears to be more strongly driven by real wages, growth and employment.

Keywords: Brazil; inequality decomposition; poverty; inflation and unemployment, education.

JL Nos.: D3, I3, N3.

1) Introduction.

Brazilian income inequality, already high by international standards, increased significantly during the 1980s[1]. Apart from being important in their own right, these increases in inequality more than offset whatever limited growth there was in the period, causing poverty to rise as well, albeit with sharp cyclical fluctuations. This paper discusses some of the factors behind the high levels of inequality, and seeks to explain its secular increase during the 1980s. It does so by means of both static and dynamic decompositions and of an investigation into the links between the behaviour of some key macroeconomic variables, on the one hand, and inequality and poverty on the other.

Section 2 contains a brief description of the data sets used in this analysis. Section 3 reports on the static inequality decompositions carried out with three inequality measures, for the years 1981, 1985 and 1990. These decompositions follow the method employed by Cowell and Jenkins (1995), and aim to separate total inequality *levels* into its components within and between groups, where the groups are defined by specific household attributes, such as regional location, urban-rural status, or age, gender, race or education of the head. This sheds some light on the structure of inequality in the population. Section 4 discusses a dynamic decomposition methodology due to Mookherjee and Shorrocks (1982), which separates *changes* in inequality into components due to changes in the mean incomes of different groups, changes in the composition of these groups, and unexplained changes.

While the results of those two sections provide some insights into the nature of Brazilian inequality, its increase during the 1980s remains mostly unexplained. Section 5 then investigates the potential role of changes in macroeconomic aggregates, such as the growth rate, the rate of inflation, the average real wage rate and the rate of unemployment. This is done by means of diagrams, correlation coefficients and OLS regressions which, despite the reduced time-series sample size, reveal some significant correlation and regression coefficients. They suggest that there may be an important link between high and accelerating inflation, and the growth of inequality. Unemployment, contrary to a widely held perception, seems to be less important. Unlike previous studies which focused on labour earnings in metropolitan areas, we work with a broader income

[1] There are many studies of inequality and poverty in Brazil during this period. The World Bank (1993) alone lists 95 references. For our own detailed analysis, see Ferreira and Litchfield (1996).

concept and a nationally representative sample. Section 6 concludes.

2) The PNAD data sets.

The data sets are the *Pesquisa Nacional por Amostra de Domicílios* (PNAD) for 1981-1990, produced by the *Instituto Brasileiro de Geografia e Estatística* (IBGE). Data were collected each year from a representative national sample of households, selected according to a three-level multi-stage sampling procedure. This is based on a successive selection of municipalities, census sectors and individual households. The total sample size varies each year, from a minimum of 286,000 (in 1986) to a maximum of 517,000 individuals (in 1985)[2].

The survey reports annually on a range of variables which form the basic data set, common to every year, with only minor exceptions. Questions are asked on subjects pertaining to the household and to individuals within the household. Information is recorded on the geographic location of the household; characteristics of the dwelling; household size; relationships between individuals in the household; activities of individuals; income from labour; income from transfers; income from other sources, such as land rents and capital incomes; occupation and other labour characteristics; age; gender; education; colour and literacy. Population weights, based on the 1980 Census, are also included.

Our definition of income is gross monthly household income per capita (from all sources) and the income receiver is the individual. One implication of this is that mean real income imputed to each individual by our procedure equals the sample mean of pre-tax income, which is in turn an estimate of mean pre-tax income in the Brazilian population. For a discussion of robustness with respect to the choice of equivalence scale, see Ferreira and Litchfield (1996).

For a country with very high inflation, such as Brazil in the 1980s, the importance of having time-series income data expressed in real terms is obvious. The unit in which the data could be expressed

[2] The sampling method embodies some natural growth in the sample size of the survey, reflecting the underlying population growth rate. There was a sharp break in 1986, when the sample size was reduced for cost-related reasons, with special care paid to maintaining precision. See IBGE (1991).

might have been the local currency, an alternative unit such as the minimum wage, or the US dollar. One of the problems with the local currency is that it changed name and unit of account three times in the relevant period[3]. Another problem is that inflation was so high that it is difficult to associate real values to the monetary values of previous periods.

The minimum wage is often used as a unit for comparing incomes over time in Brazil. But its value in real terms was far from constant during the period, detracting from its usefulness. A particular month's minimum wage value, then held constant in real terms, has also been used, though in that case the choice of the base month is arbitrary. For these reasons, and for ease of international comparability, the US dollar was chosen as the income unit. The last year in the series was chosen as the base year, for ease of current understanding of the values.

Nominal Brazilian currencies were converted to constant 1990 US dollars according to the following procedure. First, local currencies were converted into 1990 Brazilian Cruzeiros using a CPI deflator, the *INPC* (IBGE, 1993); second, the Cruzeiro series was converted to 1990 US dollars using the exchange rate for the interview month in 1990. The rate used was the period average market exchange rate for September 1990, as reported in the rf series of the IMF International Financial Statistics. For a more detailed description of the data sets and of our methodology, see Cowell, Ferreira and Litchfield (1996).

3) Static Decompositions of Brazilian Inequality.

One approach to examining the nature of inequality is to analyze the role played by certain individual characteristics, such as age, gender, education and geographic location[4]. Several theories of the distribution of income provide a rationale for investigating personal characteristics like these. Human capital theories stress the role of education, age and experience, in models where

[3] The Brazilian currency was the Cruzeiro until 1986, the Cruzado from 1986 to 1988, and the Novo Cruzado from 1988 until March 1990, when it was again renamed Cruzeiro.

[4] Whilst it is possible to draw some inferences about the direction of causality between *fixed* attributes, such as gender or race, and incomes, it is difficult to do so between *variable* attributes, such as education, and incomes.

individuals maximise utility over the life-cycle by the optimal choice of investments in human capital (Becker, 1965; Mincer, 1958). Other theories incorporate market imperfections. Labour market segmentation and dual-economy models use personal characteristics such as education, gender or geographic location, either as examples of signals which lead to discrimination, or as institutional barriers that prevent access to or mobility between different labour market segments (e.g. Lewis, 1954; Spence, 1973).

There is also empirical support for such partitions, from studies using regression analysis, inequality decompositions or analysis of variance techniques, although income inequality can never be fully explained by such characteristics. A survey of inequality decompositions in developing countries does show that personal attributes can account for large proportions of the dispersion in the distribution of income (Fields, 1980).

The analysis in this paper concentrates on five attributes of the household: its regional location; its urban/rural status; the age of the household head[5]; gender of household head; and his or her educational attainment. Decompositions are carried out for three years: 1981, 1985 and 1990. A sixth factor, ethnicity or race, is another important source of inequality. Unfortunately very little data is available on it: in 1981 the race question did not appear on the questionnaire and in 1985 less than 5% of the sample responded to it. Only for the last two or three years of the decade was there a significant response rate to the question, so that it is only included in the decomposition analysis for 1990.

The point of the static decompositions in this section is to separate total inequality in the distribution into a component of inequality between the chosen groups (I_B) - the explained component - and the remaining within-group inequality (I_W) - the unexplained component. These groups are defined by each of the attributes listed above; at first each characteristic is considered individually, and then a finer partition is created by incorporating all attributes together, to give a measure of the total inequality explained by these household characteristics.

[5] PNAD interviewers were instructed to register as household head the person "responsible for the household or so perceived by the remaining members" (IBGE, 1993, p.16).

The first partition of the overall distribution by individual attribute was carried out for age. Households were grouped into six categories by age of head: 1) under 25, 2) 25-34, 3) 35-44, 4) 45-54, 5) 55-64 and 6) 65+ years, using an extension of the categorisation in Bonelli and Ramos (1993).[6] The second partition was by educational attainment of household head, based on last completed year of formal schooling. Education was broken into five groups, again borrowing the Bonelli and Ramos (1993) categories, of 1) illiterates - less than one year of schooling, 2) elementary school - 1 to 4 years of schooling, 3) intermediate school - 5 to 8 years of schooling, 4) high school - 9 to 11 years of schooling and 5) college education - 12 or more years of schooling. The third partition was by regional location of the household. States were grouped into the five official, standard geographical regions of Brazil: North, Northeast, Southeast, South and Centre-West. The fourth partition was by whether the household was located in a rural or urban area. The fifth partition was by gender of household head. The last individual partition was for ethnicity, and only applies to 1990. Households were divided into three groups by the declared ethnicity of the household head: 1) whites, 2) black and mixed race, 3) Asian origin.

Unfortunately, many widely used inequality measures are not decomposable, in the sense that overall inequality can not be related consistently to the constituent parts of the distribution. In particular, we are interested in measures where $I_B + I_W = I$. This is not generally true, for instance, of the Gini coefficient, but it is true of all members of the Generalised Entropy class of measures (see Cowell, 1995). The general formula for the class is given by:

$$G(a) = \frac{1}{a^2 - a}\left[\frac{1}{n}\sum_{i=1}^{n}\left[\frac{y_i}{m(y)}\right]^a - 1\right], a \in \Re \qquad \textbf{(1)}$$

Because of its decomposability property, which is not shared by the Gini coefficient or by the coefficient of variation in its pure form, members of this class are clearly the most suitable for the analysis in this paper. We therefore use three measures in the decompositions below: G(0), G(1) and G(2). If α=0 then, using l'Hôpital's rule, G(α) simplifies to the mean log deviation, which is written as:

[6] Bonelli and Ramos (1993) carry out a similar set of decompositions, but only for economically active urban males between the ages of 18 and 65, working for more than 20 hours a week. Their concern is with labour earnings, rather than household incomes.

$$G(0) = \frac{1}{n}\sum_{i=1}^{n}\log\left[\frac{m(y)}{y_i}\right] \qquad \textbf{(2)}$$

Similarly, if α=1, G(α) becomes the Theil index, which is given by:

$$G(1) = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{m(y)}\log\left[\frac{y_i}{m(y)}\right] \qquad \textbf{(3)}$$

If α=2, equation 0 can be manipulated to be expressed in terms of the coefficient of variation, cv, as ½ cv^2:

$$G(2) = \frac{1}{2}\left[\frac{1}{m(y)}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - m(y))^2}\right]^2 \qquad \textbf{(4)}$$

Table 1 below gives the values for each of these measures for each of the three years analyzed in this paper. It is noteworthy that all three measures reported rise monotonically over the years cited, and are substantially higher in 1990 than in 1981. This upward trend is confirmed by a robust comparison of the disaggregated distributions, based on Lorenz dominances[7].

[7] A detailed discussion of the upward trend in inequality, including a full set of (statistically tested) stochastic dominance comparisons across every year in the decade, is contained in Ferreira and Litchfield (1996).

Table 1: Summary statistics, 1981-1990.

	1981	1985	1990
Mean Income	143	150	164
Median Income	75	74	79
G(0):mean log deviation	0.614	0.649	0.705
G(1):Theil Index	0.647	0.697	0.745
G(2):½ squared coefficient of variation	1.337	1.627	2.018

Note:all incomes in 1990 US dollars
Source: own calculations from PNAD, 1981-1990.

The values of $G(\alpha)$, $\alpha = 0, 1, 2$, for the entire distribution, may be compared with their values for different subgroups in the partitions below. Tables 2 and 3 present mean incomes, population shares, income shares and values for each of the inequality measures defined above, for each of the subgroups in each partition discussed earlier.

While these tables contain plenty of information, some basic features deserve special mention. The partition by age does not appear to be a very promising candidate for explaining much of the total inequality. The mean incomes per subgroup are fairly close to each other, varying little around the overall mean. Although households headed by the youngest do earn the least, there is no pronounced support for a life-cycle pattern of incomes. This is brought out by the mean incomes of households headed by 35-44 year-olds, in 1981 and 1985 in particular. While one might have expected these heads to be in some of their prime earning years, their household incomes per capita are lower than those of the age-groups immediately next to them. Though newborn children might explain part of this effect, it is doubtful that they account for the whole effect, particularly as most children in Brazil are born to younger household heads. Finally, the values of $G(\alpha)$ are fairly close to the overall inequalities reported in Table 1, for all three values of α, suggesting that the between-group component is not likely to be substantial.

Table 2: Summary statistics: by age, education and race of household head, 1981-1990.

	1981					1985						1990		
	μ_j	f_j	v_j	G(2)	G(1)	G(0)	μ_j	f_j	v_j	G(2)	G(1)	G(0)	μ_j	f_j	v_j
Age															
1	124	0.04	0.03	0.81	0.45	0.43	120	0.04	0.03	0.96	0.51	0.48	126	0.
2	148	0.22	0.23	1.17	0.63	0.62	153	0.23	0.23	1.32	0.65	0.64	156	0.
3	127	0.28	0.25	1.38	0.67	0.64	145	0.28	0.27	1.61	0.73	0.70	163	0.
4	146	0.24	0.24	1.32	0.63	0.60	150	0.23	0.22	1.63	0.70	0.65	169	0.
5	161	0.13	0.15	1.38	0.65	0.61	168	0.14	0.15	1.93	0.71	0.63	182	0.
6	151	0.08	0.09	1.65	0.70	0.61	151	0.09	0.09	2.01	0.75	0.63	165	0.
Education															
1	59	0.30	0.13	0.71	0.39	0.38	56	0.29	0.11	0.65	0.38	0.37	57	0.
2	109	0.46	0.35	0.71	0.41	0.41	110	0.43	0.31	1.05	0.46	0.43	114	0.
3	185	0.14	0.18	0.80	0.43	0.40	176	0.16	0.18	0.84	0.44	0.41	168	0.
4	327	0.06	0.14	0.53	0.35	0.36	310	0.08	0.16	0.65	0.38	0.37	298	0.
5	622	0.05	0.21	0.39	0.28	0.29	649	0.06	0.24	0.53	0.33	0.32	665	0.
Race															
1													220	0.
2													93	0.
3													421	0.

Notes: μ_j=mean income, f_j=population share, v_j=income share.
all incomes in 1990 US dollars
Source: own calculations from PNAD, 1981-1990.

Table 3: Summary statistics: by geographic location and gender of household head, 1981-1990.

1981						1985						1990	
μ_j	f_j	v_j	G(2)	G(1)	G(0)	μ_j	f_j	v_j	G(2)	G(1)	G(0)	μ_j	f_j
Region													
SE	190	0.44	0.59	1.06	0.56	0.53	192	0.45	0.57	1.27	0.61	0.57	21
S	146	0.16	0.17	1.09	0.55	0.51	164	0.16	0.17	1.49	0.62	0.55	17
NE	74	0.30	0.16	1.84	0.68	0.57	78	0.29	0.15	2.29	0.76	0.62	83
CW	135	0.07	0.06	1.47	0.65	0.58	159	0.07	0.07	1.80	0.68	0.60	18
N	127	0.03	0.02	1.09	0.51	0.44	155	0.03	0.03	1.61	0.60	0.52	17
Urban/Rural													
U	177	0.71	0.88	1.09	0.57	0.54	183	0.73	0.88	1.35	0.62	0.58	20
R	59	0.29	0.12	1.64	0.53	0.44	64	0.27	0.12	2.28	0.61	0.50	62
Gender													
M	144	0.89	0.90	1.35	0.65	0.62	153	0.88	0.89	1.61	0.70	0.66	16
F	133	0.11	0.10	1.24	0.59	0.55	136	0.12	0.11	1.72	0.67	0.60	14

Notes: μ_j=mean income, f_j=population share, v_j=income share.
all incomes in 1990 US dollars
Source:own calculations from PNAD, 1981-1990.

The same is true for gender, where values for the three inequality measures for each subgroup were again quite close to - and in some cases greater than - the total inequality values. It should be noted that this result - which will be confirmed by the actual decompositions in Table 4 - is not about earnings inequality between men and women in the labour market. It is based on per capita household incomes, and on a definition of household head which is open to widely different interpretations (see footnote 5). Neither does it contain any information on intra-household allocation of income or resources, so that the fact that gender of household head is unimportant in accounting for inequality should not be interpreted as a statement about either labour market or intra-household discrimination.[8]

The partitions by geographic region and by rural/urban status reveal a grater dispersion of subgroup means around the overall mean, for all years, and generally smaller values for the subgroup inequality measures than for the overall measure. There were exceptions, however, particularly for G(2) in a number of cases, and for the Northeastern region, which had higher values than the whole of Brazil for G(1) and G(2) in all three years.

But it is education that emerges as the attribute most likely to 'explain' some of total inequality. Here we see subgroup means rising monotonically with education, and displaying substantial variation around the overall mean. We also observe subgroup values for all three inequality measures well below those for the whole distribution. While this leads to the expectation that the static decomposition will reveal education as an important 'explanatory' variable, the caution raised in footnote 4 should be borne in mind: education is a variable attribute, and causation can not be inferred to run exclusively from it to the distribution of incomes. It is probably reasonable to expect that the two are determined endogenously and simultaneously, and many models do exist with prominent links between one generation's income and the level of education of the next. Since income is likely to be serially correlated across generations - although the absence of panel data

[8] Apparently, however, Brazil is not exceptional as regards the unimportance of gender of household head as a variable to explain income differences. Quisumbing et al (1995) use stochastic dominance to investigate whether poor male-headed households fared significantly better than those headed by females in ten developing countries, and were able to statistically reject that hypothesis in most cases. The notable exceptions were rural Ghana and Bangladesh.

prevents us from testing that hypothesis - and given the incompleteness in the market for credit for education, it is quite possible that education is acting partly as a proxy for parental income. Caution is certainly warranted in interpreting the importance of education in 'explaining' income inequality.

But while observing subgroup means and inequality measures can be informative, there is a more formal way to appraise the contributions of each of these household attributes to overall inequality. This is through the static decomposition analysis suggested by Cowell and Jenkins (1995), which is described below.[9] When total inequality I, as measured by any of the three indices reported in the foregoing tables, is decomposed by population subgroups, the Generalised Entropy class of measures can be expressed as the sum of within-group inequality, I_W, and between-group inequality, I_B . Within-group inequality, I_W , is calculated and weighted as follows:

$$I_w = \sum_{j=1}^{k} w_j \, G(a)_j \qquad \textbf{(5)}$$
$$w_j = v_j^a \, f_j^{1-a}$$

where f_j is the population share and v_j the income share of each subgroup j, $j=1,2,....k$. Between-group inequality, I_B, is measured by assigning the mean income of group j, $\mu(y_j)$ to each member of the group and calculating:

$$I_B = \frac{1}{a^2 - a}\left[\sum_{j=1}^{k} f_j \left(\frac{m(y_j)}{m(y)}\right)^a - 1\right] \qquad \textbf{(6)}$$

Cowell and Jenkins (1995) show that the within- and between-group components of inequality, defined as above, can be related to overall inequality in the simplest possible way: $I_B + I_W = I$. They then suggest an intuitive summary measure, R_B , of the amount of inequality explained by a particular characteristic or set of characteristics (i.e. by a partition Π:

$$R_B = \frac{I_B(\Pi)}{I} \qquad \textbf{(7)}$$

[9] Their approach draws on Bourguignon (1979), Cowell (1980) and Shorrocks (1980 and 1984).

This statistic can be interpreted as the share of total inequality which can be 'accounted for' or 'explained' by the attributes defining partition Π. Table 4 below presents values of R_B for partitions by each characteristic discussed earlier, as well as for a finer partition, incorporating all of them together. This is done for each of the three inequality indices used in this paper, and for 1981, 1985 and 1990. Clearly, the share of inequality explained by any or all of the household attributes varies according to the measure being decomposed. We focus here on G(0) and G(1). The explanatory power of the decompositions is smaller for G(2), which is more sensitive to higher incomes. In discussing the results in Table 4, the range of explanatory powers of each characteristic will be given for G(0) and G(1).

There are five main results from these decompositions: first, the explanatory power of age and gender of the household head is negligible in both cases. Second, inequality between rural and urban areas across the country explains somewhere between 10-17% of total inequality, while inter-regional differences account for 8-12%. Both of these partitions seemed to lose explanatory power with time. Third, the education level of the household head is by far the most important explanatory variable, accounting for up to 42% of total inequality in Brazil on its own. Its importance was relatively stable during the decade. Fourth, race is another important factor, accounting for between 11-13% of total inequality. The difference between the two bottom rows for 1990 shows, however, that although race is not negligible when taken alone, it must be closely correlated as an explanatory factor with some of the other attributes, since the explanatory power of the fine partition hardly changes as a result of its introduction.

Table 4: The amount of inequality explained: static results.

	1981			1985			1990		
		R_B			R_B			R_B	
	G(0)	G(1)	G(2)	G(0)	G(1)	G(2)	G(0)	G(1)	G(2)
Age	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Education	0.37	0.42	0.30	0.39	0.42	0.26	0.37	0.40	0.21
Region	0.12	0.10	0.04	0.10	0.08	0.03	0.10	0.08	0.03
Urban/rural	0.17	0.13	0.05	0.14	0.11	0.04	0.10	0.11	0.03
Gender	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Race							0.13	0.11	0.04
All (exc race)	**0.51**	**0.52**	**0.36**	**0.51**	**0.50**	**0.30**	**0.50**	**0.49**	**0.25**
All (inc race)							**0.52**	**0.51**	**0.26**

Finally, when the five main variables are taken together, so that the distribution is finely partitioned, they jointly account for about half of total observed inequality. This is quite a high proportion, in comparison with many other countries. For the United States, for instance, Cowell and Jenkins (1995) find that gender, age, race and employment status can account for 25% - 33% of total inequality, by the same method as that used here.[10] A similar range is obtained for Portugal, by Rodrigues (1993). Subject to the proviso made above that for variable factors these results can not be used to infer the direction of causation - which is particularly relevant in the case of years of schooling - this is an informative exercise.

4) The Dynamic Decomposition of Brazilian Inequality.

[10] There is a small difference: they use Atkinson indices, rather than members of the Generalized Entropy class. Higher values for R_B are obtained when equivalent - rather than mean - incomes are used to compute between-group inequality. In that case, though, $I_B + I_W \neq I$, so that R_B is no longer the only measure of explanatory power of a partition. Indeed, $R_W = 1 - I_W/I \neq R_B$.

However, while we may now feel that we know some of the factors behind the high *levels* of inequality in Brazil, such as educational attainment, geographic location, rural/urban status and race, they do not tell us anything about the reasons behind the *changes* during the 1980s. To investigate whether these household characteristics can help explain those changes, we briefly report results from a dynamic decomposition of G(0), due to Mookherjee and Shorrocks (1982).

Accounting for changes in an overall measure of inequality - such as G(0) - by means of a partition of the distribution into subgroups defined by some household attribute must entail at least two components to the change: one caused by a change in inequality between the groups, and one by a change in inequality within the groups. The first one is naturally the part of the total change 'explained' by the partition, whereas the second is a "pure inequality" or unexplained effect. But the explained component can be further disaggregated into an effect due to changes in relative mean incomes between the subgroups - an "income effect" - and one due to changes in the size or membership of the subgroups - an "allocation effect". The Mookherjee and Shorrocks (1982) procedure captures these three effects in an intuitive way. It allows the change in overall inequality to be decomposed into four terms as follows[11]:

$$\Delta G(0) = \left[\begin{array}{l} \sum_{j=1}^{k} \overline{f_j} \Delta G(0)_j \\ + \sum_{j=1}^{k} \overline{G(0)_j} \Delta f_j + \sum_{j=1}^{k} \left[\overline{l_j} - \overline{\log(l_j)} \right] \Delta f_j \\ + \sum_{j=1}^{k} (\overline{v_j} - \overline{f_j}) \Delta \log(m(y_j)) \end{array} \right] \qquad \textbf{(8)}$$

where Δ is the difference operator, f_j is the population share of group j, λ_j is the mean income of

[11] This is actually an approximation to the true decomposition, but both Mookherjee and Shorrocks (1982) and, later, Jenkins (1995) argue that for computational purposes this approximation is sufficient.

group *j* relative to the overall mean, ie $\mu(\mathbf{y}_j)/\mu(\mathbf{y})$, and the overbar indicates a simple average. The first term (a) in equation (8) captures the unexplained, or pure inequality effect. The second and third terms (b and c) capture the allocation effect, holding within-group inequality and relative mean incomes constant in turns. The final term (d) corresponds to the income effect.

By dividing both sides through by $G(0)_t$, proportional changes in overall inequality can be compared to proportional changes in the individual effects (Jenkins, 1995). It is then straightforward to draw conclusions about the importance of each effect in explaining changes in the total. Changes in terms b, c or d indicate the extent to which changes in mean incomes for the different groups, or in their composition, explain the observed changes in total G(0). Changes in the first component - the pure inequality effect - are the unexplained changes, due to greater inequality within the groups. Results for changes between 1981 and 1990 are reported in Table 5 below.

Table 5: The amount of inequality explained: dynamic results

% change in G(0)	14.8			
% accounted for by:	**a**	**b**	**c**	**d**
Age	14.9	0.1	0.0	-0.2
Education	10.0	-0.5	4.5	0.9
Region	15.2	-0.1	-0.2	-0.1
Urban/Rural	14.2	0.5	-1.5	1.7
Gender	15.0	-0.3	0.0	0.1

Notes: a shows the pure within-group inequality effect
b and c show the allocation effect
d shows the income effect

Some 5% of the total rise in inequality can be jointly accounted for by increases in mean income differences between urban and rural areas, and by offsetting migration. A more significant 33% is “explained” by reallocation and income effects across education groups. The striking feature of the table, nevertheless, is the dominance of component 'a' over all others. With the exception of education and urban/rural status, the within-group, 'pure inequality' effect of the decomposition was actually larger than the observed proportional change in G(0) for the complete distribution. This

suggests that changes in composition or relative incomes of groups defined by age, region or gender did not contribute towards the increase in overall income inequality observed in Brazil from the beginning to the end of the 1980s.

Even in the cases of education and urban/rural status, the unexplained component is still much larger than the combination of the income and allocation effects. It therefore appears that most of the growth in inequality observed in the 1980s can not be explained by changes in inequality between the groups partitioned according to the attributes in the above table.

Since ten years is a relatively short time in terms of a structural transformation of earnings behaviour, this is perhaps not surprising. But the question remains as to what lies behind the significant increases in inequality that were registered both in terms of Lorenz dominance and in terms of all scalar measures reported (see Ferreira and Litchfield, 1996), and which we now know to consist mostly of unexplained within-group effects. Standard approaches to explaining changes in the distribution of income often stop at this point, and pursue the question no further. The task is not made easier for this paper by the small number of observations in our time-series. Nevertheless, the next section presents the results of an investigation into possible links between elements of the Brazilian macroeconomic performance and the behaviour of inequality and poverty in the 1980s.

5) The Impact of Macroeconomic Performance.

While the static decomposition analysis of Section 3 shed some light on the structure of inequality by household attributes, the dynamic decompositions were incapable of explaining much of the *change* in inequality. This section changes the line of approach somewhat, and seeks to investigate whether there are any suggestive relationships between macroeconomic variables and inequality (and poverty). While in the absence of a more detailed theoretical framework, and given the limitations of the time-series data, we make no claim that these establish causation, the evidence does nevertheless strongly suggest that at least some of the (hitherto unexplained) increase in inequality in the decade was linked to macroeconomic instability, and to inflation in particular. A slightly different picture emerges for poverty, which is in line with its more cyclical behaviour.

Our findings confirm the importance of macroeconomic factors in shaping changes in the income distribution in Brazil in the 1980s, which has been highlighted by Bonelli and Ramos (1993), Urani (1993) and Cardoso, Paes de Barros and Urani (1995), among others. Generally, however, these authors have focused on the distribution of labour earnings, and relied on data from the Pesquisa Mensal de Emprego (PME) surveys, which cover only the six largest metropolitan areas in the country (Porto Alegre, São Paulo, Rio de Janeiro, Belo Horizonte, Salvador and Recife). Our approach is to focus on individual welfare, as measured by total household income per capita, rather than exclusively on labour incomes which, important though they may be, are inherently only one part of the story. In addition, we use the PNAD sample, which is representative at the state level for every state, and covers smaller urban and rural areas as well. Though there is broad agreement with earlier works on the fact that accelerating inflation was associated with increasing inequality in the 1980s[12], the impact of unemployment turns out to depend critically on the sampling universe and on the income concept analyzed. While Cardoso et al (1995) suggest that unemployment is significantly correlated with greater inequality, we find that this (rather reasonable) relationship simply does not hold in the data.[13] In the search for a macro culprit, looking at a larger data set and considering a broader income concept seems to narrow the field more tightly around inflation.

We begin by looking at the data through a series of diagrams, and computing the relevant bivariate correlation coefficients. Figure 1 plots inflation and unemployment alongside the Theil index over time. Figures 2 and 3 do the same for real wages in manufacturing and annual growth in GDP[14]. Figures 4, 5 and 6 repeat the previous three, replacing inequality (the Theil) with poverty (measured by the Foster-Greer-Thorbecke index FGT2). In each of these figures, the

[12] The agreement does not extend to the actual descriptions of inequality trends. Contrast the accounts in Cardoso et al (1995) and Ferreira and Litchfield (1996).

[13] One interesting hypothesis is that the formation of families and/or households - whatever their impact on inequality through assortive matching - may provide some insurance against unemployment risk, so that increases in the variance of the unemployment shock translate into higher dispersion in the distribution of individual labour earnings, but not so much on the distribution of household incomes. An investigation of this must be left for future research.

[14] The values of the macroeconomic aggregates used in this analysis are contained in the appendix.

macroeconomic variables are measured along the left-hand scale and the inequality or poverty indices are measured along the right-hand scale. Table 6 below reports Rank-Spearman Correlation coefficients between the Theil index and the four macro variables, and between the FGT(2) poverty measure and the same variables.

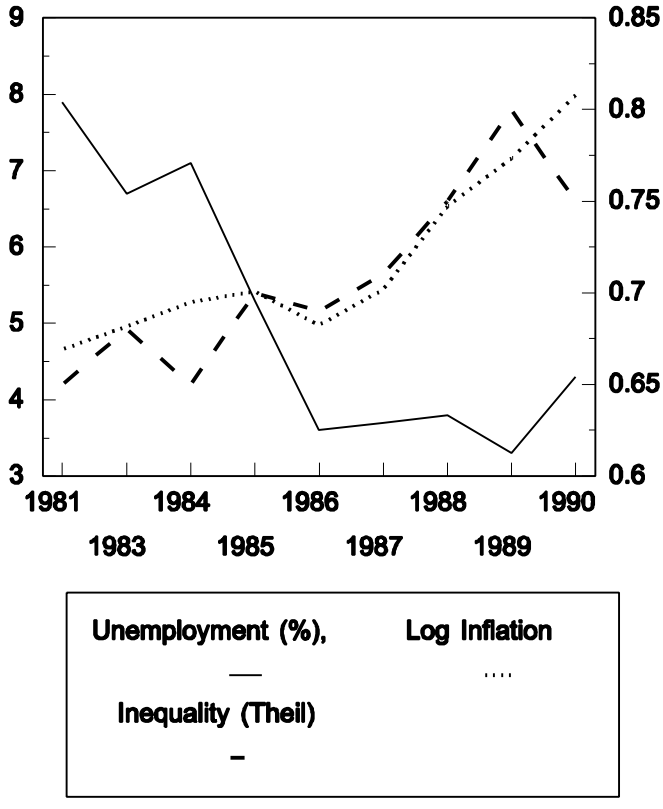

Figure 1: Unemployment, inflation and inequality, 1981-1990

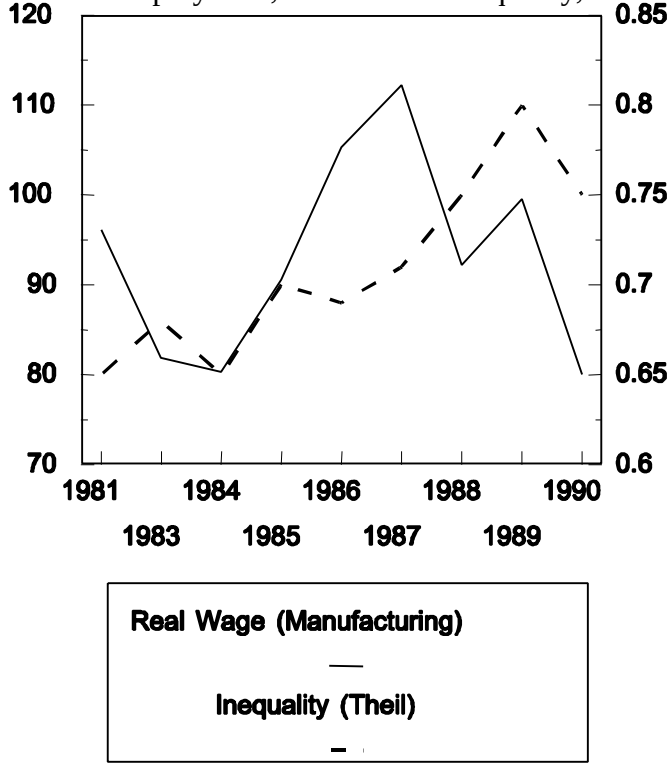

Figure 2: Real wages in manufacturing and inequality, 1981-1990

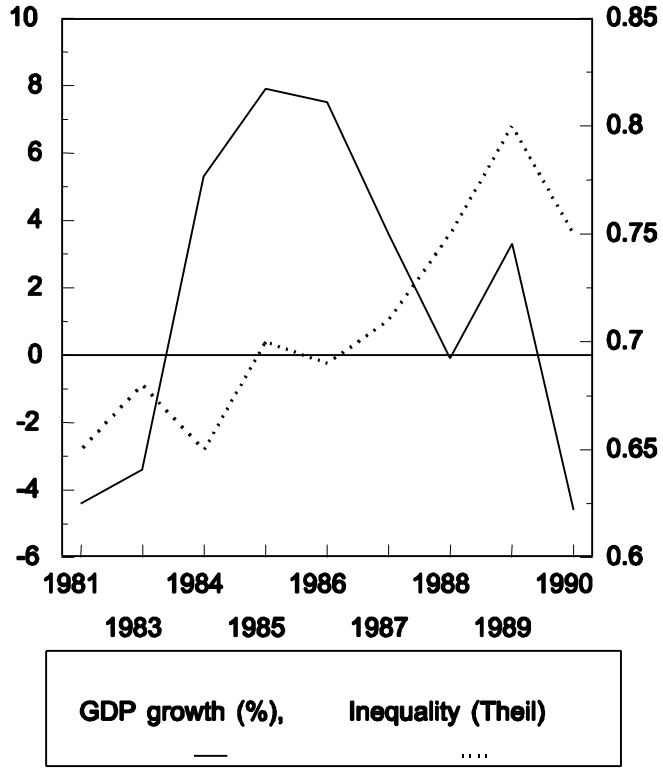

Figure 3: GDP growth and inequality, 1981-1990

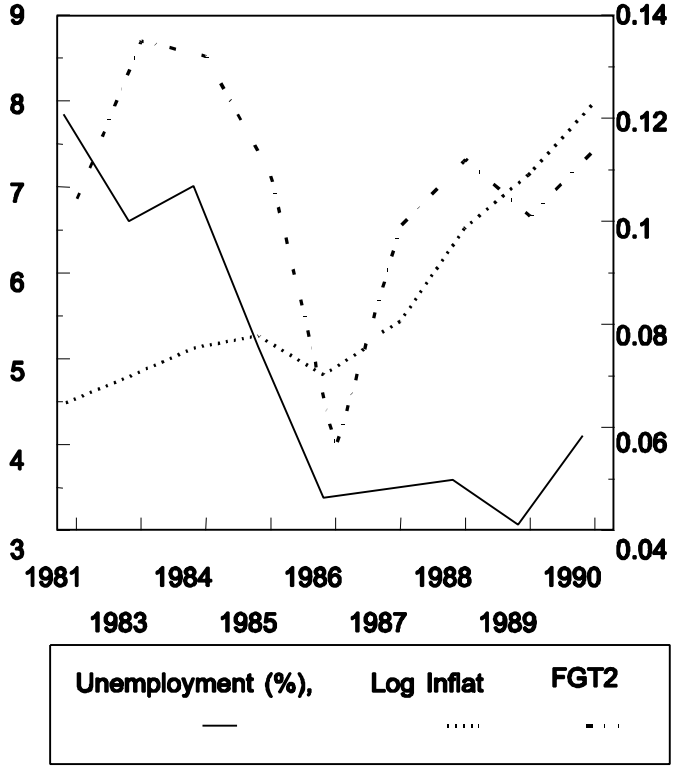

Figure 4: Unemployment, inflation and poverty (FGT2), 1981-1990

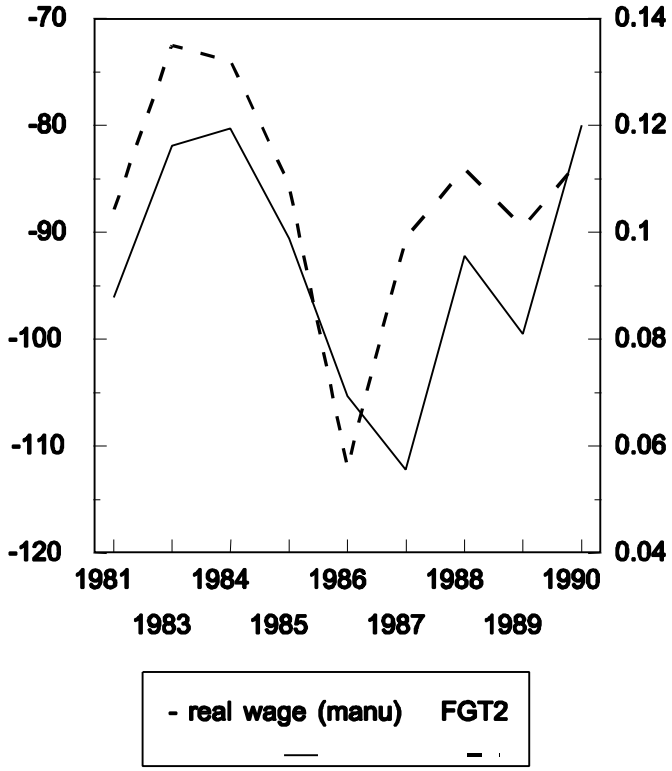

Figure 5: (Minus) Real wages (manufacturing) and poverty (FGT2), 1981-1990

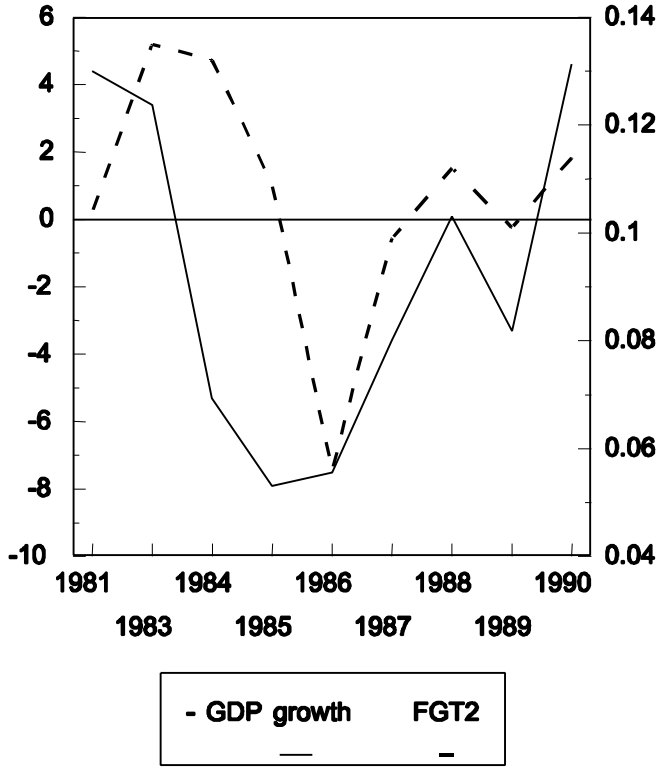

Figure 6: (Minus) GDP growth and poverty (FGT2), 1981-1990

Table 6: Correlation coefficients

	Theil index	FGT(2)
Log inflation	0.8455*	0.1038
Unemployment	-0.7986*	0.5432
Real Wage in Manufacturing	0.1592	-0.7484*
GDP growth	0.0123	-0.4349

Notes: Macroeconomic variables time-series from the Appendix.
* denotes coefficients statistically significantly different from zero at the 5% level.

It would appear from this initial look at the data that, while both poverty and inequality grew over the decade, the changes in poverty and inequality were driven by different forces. It is striking, for instance, that the signs on the correlation coefficients between the Theil and both unemployment and real wages have the 'wrong' sign. Higher unemployment was associated, in Brazil in the 1980s, with lower inequality and, despite the reduced number of observations, this negative correlation was significant. Lower real wages were also associated with lower inequality, although not significantly. Interestingly, the correlation coefficient between growth and inequality was very close to zero. The real macroeconomic force behind growth in inequality would appear to be inflation, as Figure 1 and Table 6 suggest. A reason for this has been proposed before, namely the fact that ability to hedge against inflation - i.e to protect the value of one's earnings and assets - is widely thought to be positively related to income. Not only is the inflation tax is a highly regressive means of financing a public deficit, but the poor may suffer the consequences of imperfect indexation more severely than the rich.

Neri (1995) discusses five separate channels through which higher inflation can lead to increases in

inequality, by imposing greater costs on poorer households than on richer ones. In each case, he presents substantial supportive empirical evidence from Brazil. The five channels are: (i) economies of scale in financial transactions: while shoe-leather costs may not vary with the amount involved in a financial transaction aimed at protecting assets from inflation, the benefits do. This would remain the case even if there were no barriers to entry into certain asset markets. (ii) But these barriers to entry are widespread, and mean that access to some assets particularly effective in avoiding the inflation tax are only open to depositors disposing of more substantial sums. Neri presents revealing evidence about the incidence of ownership of overnight deposits and credit cards across the distribution of income. (iii) Tighter labour markets, usually associated with higher skill levels, are better at preserving real salary values. Indexation is less perfect for unskilled, poorer workers. (iv) In addition to financial assets, one can protect the value of one's wealth against inflation by reallocating portfolio from cash to consumption goods. The effectiveness of this strategy declines with the share of goods in one's expenditure which is perishable, and this is higher for poorer households, due to Engel's law and the fact that a higher share of foodstuffs is perishable than for most other categories of goods. (v) Finally, it also depends on the storage technology available to households. Neri presents evidence on the positive correlation between freezer ownership and household income, which adds another reason why the ability to defend one's wealth against inflation increases with income.[15]

Since the dispersionary effect of high inflation is also felt within the partition groupings in Table 5 above, it may provide a candidate explanation for the large unexplained component in changes in inequality. Given the results of the dynamic decomposition reported in Section 4, it is clear that structural changes in incomes accruing to groups partitioned by age, gender, geographic location and even education, or in their composition, do not account for much of the increase in inequality shown in Table 1. In that light, a correlation coefficient of 0.85 between the Theil index and inflation, significant despite the very few observations, appears to warrant serious consideration. High and unstable inflation was perhaps the single most notable feature of the Brazilian macroeconomic scenario throughout the 1980s. Its growth and fluctuations are closely matched by

[15] While the effects of channels (iv) and (v) are not captured by PNAD income data, the first three channels affect capital or labour incomes, and their effects should therefore be registered.

those of inequality, as can be seen by Figure 1.

These tentative results are starkly at odds with the traditional view that unemployment has an inequality-augmenting effect, while inflation has an (insignificant) equalizing effect, as reported for the cases of the US by Blinder and Esaki (1978) and of the UK by Nolan (1987). It may be the case that whereas in low-inflation economies, an increase in inflation merely proxies for an increase in aggregate demand, leading to higher wages for the bottom of the distribution, in high-inflation economies such as Brazil, the regressive effect of the inflation tax dominates. Even as regards Brazil, though, we find an effect of unemployment on inequality which is at odds with the conclusions of earlier research.

The relation between poverty and the macroeconomic aggregates is rather different. The effect of inflation is still positive, but not large, while unemployment and real wages now have the expected signs. Falls in unemployment, rises in real wages and rises in GDP growth are all correlated with reductions in poverty. Indeed, the real wages index was the only variable to be significantly (negatively) correlated with the FGT(2) poverty measure.

This preliminary evidence seemed to justify further investigation, by means of a set of OLS regressions, run with the time series data used to compute the correlation coefficients above. Unfortunately, since 1982 was excluded from the PNAD sample[16], the time-series sample is very small, with only 9 observations. This adds to the list of reasons for caution in interpreting the results in this section. It also restricts the number of explanatory variables that can be included in each regression. To retain enough degrees of freedom (and reduce multicollinearity) to allow for any results to be significant, we restricted the models to be estimated to the two specifications below. Both focus on the effects of unemployment and inflation - the two variables most frequently discussed in the literature - and exclude other potential regressors.

The first model is given by:

$$y_t = a + b_1 UE_t + b_2 IF_t + u_t \qquad \textbf{(9)}$$

[16] See Cowell, Ferreira and Litchfield, 1996.

where the dependent variable y_t is either the Theil Index or the Foster-Greer-Thorbecke (α=2) at time t, UE is the rate of unemployment (percent) and IF is the logarithm of the rate of inflation (percent). The second model was designed to replicate the Blinder and Esaki (1978) approach[17], which was also applied to UK data by Nolan (1987). It is given by:

$$s_{it} = a_i + b_{1i} UE_t + b_{2i} IF_t + u_{it} \qquad \textbf{(10)}$$

where s_{it} denotes the income share of the ith decile in year t, and the regressors are the same as in (9). The subscript i associated with the intercept and the coefficients indicates that these are being estimated separately for each decile. The ten decile share regressions are in fact a set of "seemingly unrelated regressions" (Zellner, 1962), but since the right-hand-side variables are the same in each equation, the SURE estimation technique suggested by Zellner is equivalent to the OLS procedure, which is used to estimate the equations. See Nolan (1987) for details of the approach. Table 7 below presents the basic OLS estimation results for (9) and (10).

These regressions add strength to the suggestion that macroeconomic instability was an important factor behind the increase in Brazilian inequality in the 1980s. The Durbin-Watson test for residual autocorrelation generally fails to reject the null hypothesis that the problem is not present, which eliminates the most likely cause of bias in the coefficients. The R^2 values are sufficiently large that the F-test for joint significance rejects the null hypothesis of no relation at the 5% level for nine out of the ten decile regressions. For the bottom four deciles and the top one, the F-test rejects the null at the 1% level, as it does for the inequality version of model (9). There are also a number of individual coefficients which are significantly different from zero at the 5% level (Student's t test).

[17] There are two small differences between their formulation and ours. First, their dependent variables are quintile shares, whereas we use decile shares. Second, they include a time trend as a regressor. This was done for our data, and the results were similar in nature to those presented below, but there was considerable cost, in terms of significance, from losing a precious degree of freedom and introducing some multicollinearity.

Table 7: OLS Regression Results

OLS Estimation of Model (9)

y	$\hat{ß}_1$ (UE)	$\hat{ß}_2$ (IF)	R^2	Durbin-Watson
Theil Index	-0.014**	0.023**	0.878[ff]	2.228[a]
FGT(2)	0.012**	0.012	0.549	2.211[a]

OLS Estimation of Model (10)

Decile	$\hat{ß}_1$ (UE)	$\hat{ß}_2$ (IF)	R^2	Durbin-Watson
1	0.029	-0.063**	0.787[ff]	1.547[b]
2	0.034*	-0.089**	0.868[ff]	2.024[a]
3	0.028	-0.112**	0.836[ff]	2.189[a]
4	0.032	-0.129**	0.836[ff]	2.208[a]
5	0.028	-0.126**	0.752[f]	2.249[a]
6	0.016	-0.137**	0.734[f]	2.295[a]
7	0.023	-0.121**	0.735[f]	2.145[a]
8	0.039	-0.054	0.690[f]	2.265[a]
9	0.077*	0.048	0.487	2.908[b]
10	-0.305	0.779**	0.830[ff]	1.971[a]

Notes: * denotes statistically significantly different from zero at the 10% level.
** denotes statistically significantly different from zero at the 5% level.
a: The Durbin-Watson test (5% level) fails to reject the no autocorrelation hypothesis.
b: The Durbin-Watson test statistic is in the inconclusive range. (For n=9, k=2, d_L=0.629, d_U=1.699)
f: The F test for the joint significance fails to reject the null of the no joint significance at the 5% level.
ff: The F test fails to reject the null at the 1% level.

More specifically, there is substantial backing for the hypothesis that high inflation may have contributed to the rise in inequality - through the regressivity of the inflation tax and imperfect indexation. The first equation of model (9), whose joint explanatory power is significant at the 1% level, confirms the positive coefficient of inflation, which is significant at the 5% level. (So is the counter-intuitive negative coefficient of unemployment, to which we turn next.) The Blinder-Esaki equations in model (10) are even more revealing. The coefficients in these ten regressions suggest

that the impact of inflation, *ceteris paribus*, would have been to reduce the shares of the bottom eight deciles of the distribution, and to raise the shares of the top two. But, as we show in Ferreira and Litchfield (1996) this is precisely what happened to the Brazilian distribution from 1981 to 1990: the richest two deciles gained income share at the expense of the bottom eight. And, despite the small sample size, the inflation coefficients are significant (at the 5% level) for the bottom seven and the top one deciles.

By contributing to a reduction in the income shares of the poor, inflation should clearly have a positive impact on any measure of poverty as well. This is confirmed by the sign of its coefficient in the second version of model (9). There is also confirmation, however, of the hypothesis that inflation and unemployment are less closely related to poverty than to inequality: the F-test for this regression fails to reject the null hypothesis of no relation at the 5% level. This might have been expected, since the real wage index, which had the only significant correlation coefficient with FGT(2), was not included in this regression.[18]

What about the effects of unemployment? The conventional wisdom has been to expect unemployment to be positively related to inequality and to poverty. This is the case in most countries. As Nolan (1987) states:

> "These results [for the US, the UK and Canada] are in line with the a priori expectation that unemployment reduces the share of the bottom groups." (p.21).

For Brazil too, as we have mentioned, the incipient consensus was that unemployment led to greater dispersion: "Our results support the hypotheses that unemployment increases inequality..." (Cardoso et al, 1995, p.168). It turns out, however, that those results seem to apply only to labour earnings in metropolitan Brazil, and not to extend to a broader income concept and the country as a whole. In this more general context, although unemployment is positively (and significantly) related with poverty, it is negatively related with inequality. And it seems to increase the shares of the bottom nine deciles, at the expense of the richest one.

---

[18] This exclusion was motivated by the small sample size and for comparability across the models.

There are two possible explanations for this counter-intuitive phenomenon. The first is that the macroeconomic history of the decade was such that unemployment and inflation were negatively correlated between themselves (as inflation rose during the decade, unemployment fell), and that the apparent positive effect of unemployment on the shares of the poor is capturing some of the real (negative) effect of inflation. This argument is reinforced by the fact that when unemployment and inflation are included together in the decile regressions, the inflation coefficients are generally significant (eight of them at the 5% level), whereas the unemployment coefficients are not. This suggests that the real macroeconomic culprit for increasing inequality is inflation, and that the positive coefficient of unemployment on the FGT(2) regression of model (9) - which is significant - is a better guide to the effects of unemployment on the poor than the (insignificant) positive coefficients in the decile share regressions.

The second candidate explanation is that unemployment in Brazil - and possibly in other developing countries with large informal sectors and undeveloped social safety nets - is not a labour status likely to be reported by the very poorest. They may respond to negative labour demand shocks by retreating to an informal sector characterised by self-employment with low productivity rates, or by employment at flexible wages. This is the view of unemployment as a 'luxury' which the very poor in a developing country can not afford. Further empirical investigation of this possibility is outside the scope of this section, but if it were found to contain some truth, this may also help explain the correlation between reductions in unemployment and income share losses by the poor. It could be that the direction of causation is reversed, with lower income shares meaning that some people can no longer afford to remain unemployed - in which state the expected present discounted value of their future search prospects may be higher - and must move to a (lower utility) informal sector employment.

While this section has raised some new questions, it has also pointed to at least one important candidate answer. The results presented in Section 4 indicate that the structural or microeconomic factors usually included in dynamic inequality decompositions can not account for much of the change in this period. This section has discussed some suggestive evidence that inflation may have been the most important factor behind the increase in Brazilian inequality in the 1980s. Poverty, on the other hand, appears to have been more closely related to real wages, unemployment and

growth.

Unlike earlier research on this topic, we have not found that unemployment is associated with greater inequality in household incomes. There appears to be scope for future work, both theoretical and empirical, on the effects of unemployment on both poverty and the distribution of income, to investigate the apparent contradiction between its direct (and expected) effect on poverty and its counter-intuitive apparent negative effect on inequality.

6) Conclusions.

This paper has sought to explain both the structure of and the upward trend in Brazilian inequality. To do so, it relied on a mixture of conventional decomposition techniques, which focus on more microeconomic or structural factors, and a simple econometric analysis of the role of macroeconomic variables. Whereas the decompositions partition the distribution according to various characteristics of the household, such as geographic location and head's age, gender, race or education, the econometric estimations look for relationships between inequality and poverty measures on the one hand, and macroeconomic indicators such as inflation and unemployment on the other.

The static decomposition method, which followed Cowell and Jenkins (1995), revealed that the set of household attributes described above, taken together, was capable of 'explaining' about half of overall inequality as 'between groups'. Taken individually, education was the most important explanatory factor, accounting for 37-42% of overall dispersion on its own. Causality can not be inferred, but the finding is descriptively significant. Race, regional location and urban/rural status also accounted for some 10% of total inequality each, but age and gender of head were unimportant as sources of inequality.

While some light was thereby shed on the *structure* of Brazilian inequality, partitions by household characteristics were less successful in explaining *changes* in the distribution. The dynamic decomposition due to Mookherjee and Shorrocks (1982) found that changes in the composition of education groupings - notably an increase in the numbers of intermediate and high-school graduates

- had some impact on the overall increase in inequality. But its main result was that most of the increase in overall inequality between 1981 and 1990 was due to an unexplained, 'pure inequality' effect.

This result prompted consideration of a different set of possible factors influencing the income distribution: macroeconomic fluctuations. These factors had been considered before, both for developed economies and for Brazil, but our findings highlight some differences. Possibly as a result of the severity of the macroeconomic instability prevailing in the 1980s, Brazilian inflation seems to have had a much more detrimental impact on the distribution of income than was found for the US or the UK. Also, when one considers the national distribution of household income per capita, unemployment is at best an insignificant explanatory variable for inequality (and at worst negatively associated with it). All this suggests that increases in (an already high) level of inflation are the most important correlates with, and may be partly responsible for, increases in inequality and a redistribution of income shares from the poor and the middle classes to the rich.

Although the analysis in this paper is more ambiguous about the effects of unemployment on income dispersion, it appears to be significantly related to increases in absolute poverty. Poverty also appears to increase with inflation, albeit less markedly and less significantly than inequality. Bivariate correlation coefficients suggest that real wage cuts and reductions in economic growth also appear to be associated with increases in poverty.

If the study of the distribution of incomes in Brazil during the 1980s brings any one lesson, it is that macroeconomic instability is bad for the poor. While the government should seek to reduce disparities in the access to education and introduce policies to combat race discrimination wherever it exists, it should never do so at the expense of the fiscal and monetary discipline which underlies macroeconomic stability. Claims that there are 'social' reasons which justify the adoption of fiscally irresponsible policies, which may lead to a resumption of inflation and consequently to a reduction in sustainable growth rates and employment opportunities, ignore the substantial evidence that the subsequent costs are born disproportionately by the poor. Brazil has a very unequal distribution of income, and it must address the structural factors which underpin it, beginning with educational opportunities. But it must do so within the macroeconomic constraints which ensure low inflation,

macroeconomic stability and sustainable growth.

References.

Becker, G.S. (1965): "A Theory of the Allocation of Time", Economic Journal, **75**, pp.493-517.

Blinder, A. and H. Esaki (1978): "Macroeconomic Activity and Income Distribution in the Postwar United States", Review of Economics and Statistics, **LX(4)**, pp.604-9.

Bonelli, R. and L. Ramos (1993): "Income Distribution in Brazil: an evaluation of long-term trends and changes in inequality since the mid-1970s", paper presented to the 12th Latin American Meeting of the Econometric Society, Tucuman, Argentina, August 17-20th, 1993.

Bourguignon, F. (1979): "Decomposable Income Inequality Measures", Econometrica, **47**, pp.901-20.

Cardoso, E., R. Paes de Barros and A. Urani (1995): "Inflation and Unemployment as Determinants of Inequality in Brazil: the 1980s", Chapter 5 in Dornbusch, R. and Edwards, S. (eds): Reform, Recovery and Growth: Latin America and the Middle-East; (Chicago: University of Chicago Press for the NBER).

Cowell, F.A. (1980): "On the Structure of Additive Inequality Measures", Review of Economic Studies, **47**, pp.521-31.

Cowell, F.A. (1995): Measuring Inequality, 2nd edition, (Hemel Hempstead: Harvester Wheatsheaf).

Cowell, F.A., F.H.G. Ferreira and J.A. Litchfield (1996): "The Evolution of Income Distribution in Brazil during the 1980s: Documentation and Procedures", LSE mimeo.

Cowell, F.A. and S.P. Jenkins (1995): "How much inequality can we explain? A methodology and an application to the USA", Economic Journal, **105,** pp.421-430**.**

Fields, G.S. (1980): Poverty, Inequality and Development, (Cambridge: Cambridge University Press).

Ferreira, F.H.G. and J.A. Litchfield (1996) "Growing Apart: Inequality and Poverty Trends in Brazil in the 1980s", LSE DARP Discussion Paper No.23 (August).

Instituto Brasileiro de Geografia e Estatística (IBGE) (1991): *Para Compreender a PNAD,* (Rio de Janeiro: IBGE).

Instituto Brasileiro de Geografia e Estatística (IBGE) (1993): Pesquisa Nacional por Amostra de Domicílios: Síntese de Indicadores da Pesquisa Básica - 1990, (Rio de Janeiro: IBGE).

Inter-American Development Bank (IDB) (1991, 1994): Economic and Social Progress Report, (Washington: IDB).

Jenkins, S.P. (1995): "Accounting for Inequality Trends: Decomposition Analyses for the UK, 1971-86", Economica, **62,** pp.29-63.

Lewis, W.A. (1954): "Economic Development with Unlimited Supplies of Labour", Manchester School, **22**, pp.139-191.

Mincer, J. (1958): "Investment in human capital and personal income distribution", Journal of Political Economy, **66**

Mookherjee, D. and A. Shorrocks (1982): "A Decomposition Analysis of the Trend in UK Income Inequality", Economic Journal, **92,** pp.886-902.

Neri, M. (1995): "Sobre a Mensuração dos Salários Reais em Alta Inflação", Pesquisa e Planejamento Econômico, **25**, no. 3, pp.497-525.

Nolan, B. (1987): Income Distribution and the Macroeconomy, (Cambridge: Cambridge University Press)

Quisumbing, A.R., L. Haddad and C. Peña (1995): "Gender and Poverty: New Evidence from Ten Developing Countries", FCND Discussion Paper No. 9, IFPRI, Washington.

Rodrigues, C.F. (1993): "Measurement and Decomposition of Inequality in Portugal, 1980/81-1989/90", CISEP Discussion Paper 1993-1, Lisbon.

Shorrocks, A.F. (1980): "The Class of Additively Decomposable Inequality Measures", Econometrica, **48**, pp.613-25.

Shorrocks, A.F. (1984): "Inequality Decomposition by Population Subgroup", Econometrica, **52**, pp.1369-85.

Spence, M. (1973): "Job Market Signaling", Quarterly Journal of Economics, pp.355-374.

Thomas, J.J. (1995): "The New Economic Model and Labour Markets in Latin America", Ch.4 in V. Bulmer-Thomas (ed) (forthcoming): The New Economic Model in Latin America and Its Impact on Income Distribution and Poverty, (London: Macmillan)

Urani, A. (1993): "Inflação e Desemprego como Determinantes do Nível e da Distribuição da Renda do Trabalho no Brasil Metropolitano; 1982-1992", IPEA Série Seminários no. 04/93, Rio de Janeiro.

World Bank (1993): Social Indicators of Development, 1993, (Washington: The World Bank).

Zellner, A. (1962): "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias", Journal of the American Statistical Association, **57**, pp.346-368.

Appendix: Macroeconomic Indicators

	1981	1982	1983	1984	1985	1986	1987	
GDP per capita (1988 US$)[a]	2,252	2,237	2,145	2,118	2,235	2,362	2,394	2,3
Annual growth in GDP (%)[b]	- 4.4	0.6	-3.4	5.3	7.9	7.5	3.6	-0.
Open Unemployment (%)[c]	7.9	6.3	6.7	7.1	5.3	3.6	3.7	3.
Annual Inflation Rate (%)[a]	106	98	142	197	227	145	230	68
Real wages in manufacturing (1980= 100)[c]	96.1	97.7	81.9	80.3	90.6	105.3	112.2	92

Notes: [a] Source for 1981-1983: IDB (1991). Source for 1984-90: IDB (1994). Due to data revision, there are some d series reported in the two volumes above, but these are not too great.

[b] Source: IDB (1991), p.54.

[c] Source: Thomas, J.J. (1995). Open unemployment is an annual average of monthly data for the metropolit Janeiro, Belo Horizonte, Porto Alegre, Salvador and Recife.