DISTINGUISHING CHRONIC POVERTY FROM TRANSIENT POVERTY IN BRAZIL: DEVELOPING A MODEL FOR PSEUDO-PANEL DATA*

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ABSTRACT

Although many studies have addressed poverty in Brazil, very few of them have analyzed the dynamic nature of this phenomenon. In order to fill this gap, this Working Paper seeks to identify the features that determine the permanence of poverty and the downward mobility into poverty of adults in urban areas. Due to the scarcity of Brazilian panel surveys, we use a 'pseudo-panel' obtained from *PNAD*, a cross-sectional National Household Survey. The probabilities of staying in states (poor or non-poor) and changing states (such as from poor to non-poor) are estimated with a bivariate probit for grouped data. Our analysis distinguishes between persistent and observed components that can condition the probability of being poor and helps identify the groups that are particularly affected by either transient or chronic poverty. We find that between 1995 and 2003, 73 per cent of urban relative poverty in Brazil was chronic and most of this level was due to an initial persistent condition of poverty. In other words, most poor people are subject to poverty mainly because of their past persistent condition of poverty. These findings suggest that an effective policy of reducing poverty should involve not only a systematic multi-sectoral approach, such as improving human capital and the access to public services, but also an extensive programme of income redistribution.

Keywords: Chronic Poverty and Transient Poverty; State Persistence and State Transition; Endogenous Switching Probit Model; Pseudo-panel; Brazil.

JEL Classification: C35, C51, I32

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* The authors would like to thank Terry McKinley for serving as the internal peer reviewer of this working paper and Armando Barrientos, Phillippe Leite and Sergei Soares for serving as the external peer reviewers. Helpful comments were also received from Valéria Pero, Ana Maria Hermeto de Oliveira, Simone Wajnman and André Golgher.

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1 INTRODUCTION

Studies on poverty in Latin America have revealed that some specific groups in the population are most likely to be poor, such as: people of African descent, indigenous groups, individuals with little schooling, undocumented workers (especially children and teenagers) and households that have a large numbers of dependents or are headed by individuals with little or no formal education (IADB, 1998; World Bank, 2003).

In Brazil, poverty is not homogeneously spread throughout its many regions. No matter what indicator is used, poverty incidence is much higher in the North and Northeast regions. Over the past thirty years, in part due to rural-urban migration, poverty has increasingly become an urban and metropolitan phenomenon, even though its incidence continues to be higher in rural areas. According to Rocha (2003), by the late 1990s, the urban poor accounted for 78 per cent of the total in Brazil.

Studies that have analyzed the poverty profile in Brazil through a static analysis of households, such as Rocha (2003) and Ferreira et al. (2000), present similar results. Nevertheless, if poverty is regarded as a dynamic phenomenon, this type of analysis provides an incomplete record of its profile. Taking into account that about 35 per cent of the population is currently poor (Rocha, 2003), we should be interested in distinguishing between those population groups that are persistently poor and those that are only temporarily poor.

As in other developing countries (Deaton, 1997), the dearth of studies on poverty dynamics is due to the scarcity of panel data.[1] In light of this problem, the main objective of this Working Paper is to identify the characteristics of groups that contribute to their permanence in poverty or their tendency to downward mobility into poverty. The state of 'permanence in poverty' is determined by the proportion of the poor in the last time period who currently remain in poverty. The downward mobility rate is defined as the proportion of the non-poor in the last period who have fallen into poverty. In order to identify such trends, this paper uses a Markov model, which involves estimating individual probabilities of transiting from a state (such as poverty) or remaining permanently in it, based on an endogenous switching probit model. Such a methodology is similar to that used by Stewart and Swaffield (1999) and Cappellari and Jenkins (2004). The difference is that while these studies used panel data, we use 'pseudo-panel' data. In addition, we seek to distinguish chronic poverty from transient poverty based on the estimated parameters of our regression model.

Bourguignon et al. (2004), Gibson (2001), and Suryahadi and Sumarto (2003) used various methods for estimating the dynamic aspects of poverty without panel data. However, the first study assessed vulnerability to poverty *ex-ante*; it did not analyze *ex-post* the determinants of mobility into or out of poverty. The other two studies decomposed observed poverty into chronic and transient proportions through a cross-sectional method. Nonetheless, Gibson's method requires not only cross-sectional data but also a subset of repeated observations, while Suryahadi and Sumarto's method does not make any attempt to decompose chronic and transient poverty longitudinally.

To overcome the problem of a lack of panel data, we have opted for a 'pseudo-panel' analysis. Even though the Brazilian household survey (*Pesquisa Nacional por Amostra de Domicílios*, PNAD) does not enable us to conduct a dynamic analysis of individuals, we can still construct homogenous social groups and analyze their behaviour over time. This approach has been suggested by Deaton (1985) and Verbeek and Nijman (1992). Thus, we have constructed a 'pseudo-panel' of 180 cohorts of urban adults based on their date of birth, sex, race, schooling and location. Using six waves of the PNAD survey (1993, 1995, 1997, 1999, 2001, and 2003), we have estimated the joint likelihood that individuals of a particular cohort remain in poverty or fall into it over time.

We find that between 1995 and 2003, 73 per cent of urban relative poverty in Brazil was chronic and that most of this level was due to a 'path dependence' effect. Our definition of relative poverty assumes that the poor are those who earn less than some proportion (such as 60 per cent) of the median equivalent income per person for each year. Path dependence suggests that most of the urban poor remain in poverty primarily because they were previously persistently poor. Among the most prone to chronic poverty are nonwhites, the least educated, residents in the Northeast region and informal workers. Transient poverty is more concentrated among women and households headed by them. People living in a household headed by an unemployed worker are also prone to transient poverty.

The rest of this Working Paper is divided into five main sections and a conclusion. The second section presents a review of the literature that addresses the distinction between chronic and transient poverty. The third section defines the measures of a minimum standard of well-being that we use in our study. The model specifications are presented in the fourth section, including the description of the theoretical framework, the empirical method of analysis and the sources and treatment of data. The empirical results are presented in the fifth section. The paper ends with concluding remarks.

2 CHRONIC AND TRANSIENT POVERTY

The standard definition of chronic poverty specifies it as an individual experience of deprivation that lasts for a long period of time (Hulme and Shepherd, 2003). According to Barrientos et al. (2005), there are three main definitions of chronic poverty in the literature. The first approach emphasizes the duration of poverty. It identifies the chronic poor as those with per capita income (or consumption) levels persistently below the poverty line during a long period of time. Transient poverty is associated with a fluctuation of income around the poverty line (Gaiha and Deolalikar, 1993). The second definition, called the 'component approach', distinguishes between the constant component of income or consumption (the determinant of chronic poverty) and the fluctuating component (the determinant of transient poverty) (Jalan and Ravallion, 1998 and 2000). The third approach considers current income and its variability among groups or households in order to estimate the probability of future shortfalls in income (Pritchett et al., 2000; Bourguignon et al., 2004).

Since the publication of Ravallion's 1988 paper, various techniques of dynamic assessment have been proposed in the literature on poverty. However, only a few of them have sought to overcome the problem of scarcity of panel data. Among them are the studies of Bourguignon et al. (2004), Gibson (2001) and Suryahadi and Sumarto (2003), which have already been mentioned in the introduction.

Chronic poverty can be analyzed in terms of either absolute or relative deprivation. Although most studies in the literature examine absolute chronic poverty, Yaqub (2003) argues that with regard to individuals who are persistently located around the same quantile of the income distribution, relative chronic poverty could be as difficult to escape as absolute chronic poverty – if not more difficult.

According to McKay and Lawson (2002), the characteristics most commonly associated with chronic poverty include (among others):[2] lack of human capital, the demographic composition of households, location of residence, lack of ownership of physical assets and low-paid labour. One would expect transient poverty to have different features. However, some factors such as human capital and physical assets are important for both types of poverty. Among factors that contribute to the transience of poverty are: family size, government transfers, seasonality of economic activities, migration and life cycle events. Empirical evidence strongly suggests that transient poverty is associated with the inability of families to maintain their consumption level when facing fluctuations or shocks that adversely affect their incomes or individual circumstances (Jalan and Ravallion, 1998).

In addition to the individual and household characteristics that contribute to the greater probability of poverty, another explanatory factor is 'state dependence'. According to Giraldo et al. (2002), two distinct factors generate the persistence of poverty. The first, as pointed out above, is the heterogeneity among individuals since each person exhibits a different set of characteristics. The second factor is that the previous experience of deprivation over a significant period of time tends to make individuals more prone to poverty over successive periods. That is, previous poverty may be a determinant of current poverty, independently of individuals' characteristics. Since Heckman's work (1978), this second condition has acquired the labels of True State Dependence (TSD) or Genuine State Dependence (GSD), as indicated by Arulampalam et al. (2000) and Cappellari and Jenkins (2004). The observed level of state dependence that results from both processes is called Aggregate State Dependence (ASD). Since GSD is a measure of immobility that controls for observed and unobserved heterogeneities of individuals, the difference between ASD and GSD levels is due to taking account of individuals' characteristics.

The distinction between chronic and transient poverty and the identification of the specific determinants of each imply that public policies cannot be uniformly applied (Gaiha and Deolalikar, 1993; Barrientos et al., 2005). Analysis of fluctuations into and out of a state of deprivation is important in order to formulate effective policies against poverty. Regarding this aspect, Hulme and Shepherd (2003) argue that short-term interventions in the labour market, whose emphasis is the creation of opportunities for those who are able to escape their precarious condition and maintain non-poor livelihoods, are not effective against chronic poverty. In addition, the heterogeneity of the experiences of chronic poverty and the diverse factors that contribute to it suggest that policies have to be context-specific. The paper by Giraldo et al. (2002) points out that the difference between ASD and GSD is critical. For example, if persistent poverty is caused mainly by GSD, cash transfer programmes might be effective if they substantially increase the income of poor households. Otherwise, if persistent poverty is caused mainly by individuals' characteristics, such monetary transfers might not be effective because they do not change the adverse attributes of individuals and households (such as lack of education or assets).

3 EQUIVALENT INCOME AND POVERTY LINE

Poverty can be defined through monetary parameters, such as income and consumption expenditure, or non-monetary dimensions, such as education, anthropometry and mortality

(Sahn and Stiffel, 2000; Baulch and Masset, 2003). This paper focuses on changes in monetary indicators of deprivation that occur over the short and medium term and which might or might not persist over the long term.[3]

When a monetary indicator is used as a measure of well-being, two variables can normally be utilized, i.e., consumption expenditure or available income (Deaton, 1997). Although expenditures can more directly capture the current level of well-being of the household, there is often a lack of information on expenditures related to access to services or property. This is the case for data from Brazil's household survey, the PNAD. Consequently, income is frequently used as an indicator of well-being. This study uses total household income per capita and then modifies this variable by using scale parameters for the members of each household. This creates what is known as 'equivalent household income', or simply 'equivalent income'.

Thus, this paper first considers per capita household income, in which all members of the household have the same weight in the denominator. Then it uses as a scaling factor the square root – i.e., it divides total household income by the square root of the number of members (similar to the method used in Buhmann et al., 1988). The results from these two methods are compared in order to take account of the effects of household scale economies. In addition, we use other methods, such as the OECD and the McClements scales, in order to take account of differences in the age composition of households (Muellbauer, 1977).

This Working Paper defines the poor as those individuals who have an equivalent income below a specified poverty line and the non-poor as individuals with an equivalent income equal to or above this line. We have utilized primarily measures of relative deprivation. Thus, we define a poverty line as 60 per cent of the median equivalent household income per capita for each year and for each scale cited above. In order to test the robustness of our results, we also consider other percentages, such as 50, 70 and 80 per cent. In order to compare differences due to using a relative or absolute definition of poverty, we have also produced results based on using lines for absolute poverty and indigence, as applied by Rocha (2003).

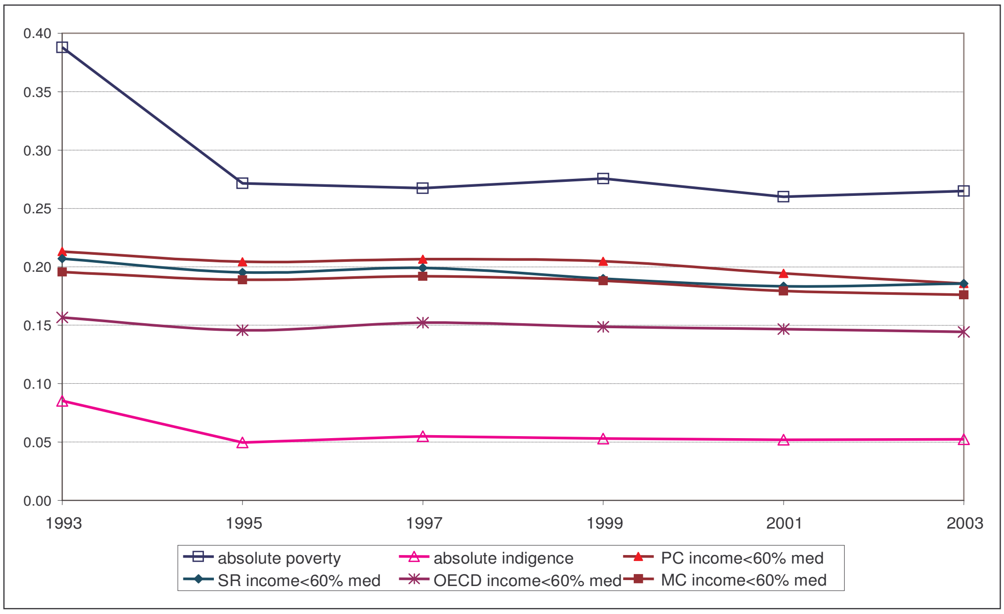
Graph 1 illustrates the evolution between 1993 and 2003 of the poverty headcount ratio in Brazil according to various poverty lines. The headcount index exhibits a fairly uniform pattern when relative deprivation measures are used**.** However, when measures of absolute deprivation are used, there is a decrease in the proportion of the poor during the period 1993-1995, after the '*Plano Real*',[4] and a fairly constant proportion of the poor thereafter.

According to Rocha (2003), the macroeconomic stabilization in 1994 was a threshold between two distinct levels of incidence of absolute deprivation in Brazil.[5] The research of Ferreira and Litchfield (2000), Ramos and Vieira (2000) and Barros et al. (2000) have shown that the income distribution in Brazil is characterized by persistently high inequality, with a slight non-monotonic tendency to rise during the last two decades—at least until 2003. Therefore, relative poverty might tend to be more persistent than absolute poverty. This aspect reinforces our choice to use measures of relative deprivation rather than absolute deprivation.

Our estimates of poverty using an adjustment based on the square root scale are lower than for the unitary scale (i.e., for income per person). Using the OECD and McClements scales gives even smaller estimates of poverty than the square root scale. These estimates merely confirm how results can differ when different methods are used.

GRAPH 1

Poverty headcount evolution in Brazilian urban areas based on different poverty measures from 1993 to 2003



Note: absolute lines from Rocha (2003), PC = per capita, SR = square root and MC = McClements

Source: own elaboration based on PNAD data and Rocha (2003).

4 MODEL SPECIFICATION AND DATA SOURCES

Our Transient-Chronic analysis (henceforth T-C) is based on the component approach (e.g., comparing constant versus fluctuating components of a poverty index). It considers the distinction between a stationary or permanent component and a transient component, both of which contribute to the propensity to poverty of each cohort. In contrast to the empirical analysis proposed by Ravallion (1988) and Jalan and Ravallion (1998, 2000), our study does not identify the two factors on the basis of income or expenditure components. Rather, the Transient-Chronic components are predicted based on the propensity to poverty that is due to the persistent characteristics of individuals and their state dependence.

InSection 4.1 below, we present a T-C decomposition model, in which chronic poverty is a function of a stationary income component and transient poverty is due to the deviation from this stationary value. However, we do not need to observe past income to estimate stationary (chronic) poverty. Transforming the dynamic income process in a discrete Markov process, we need merely to observe the past poverty index. In a pseudo-panel analysis, it is easier to deal with cohort poverty measures than with income distribution within the cohort. The empirical strategy to estimate the Markov process for cohorts is presented in Sections 4.2 and 4.3 and the description of the data in Section 4.4.

4.1 THEORETICAL FRAMEWORK

Based on the model developed by Ravallion (1988), the well-being of individual *j* in time *d* is given by:

$$y_{jd} = \vartheta(x_j, \eta_d), \quad \vartheta_x > 0 \text{ and } \vartheta_\eta > 0,$$

where the function ϑ is at least two times differentiable, and x_j and η_d are the determinants of the equivalent income.

The function ϑ can be interpreted as an indirect utility function in x_j, a vector of time-constant individual features, and η_d, a random variable with mean zero. According to Ravallion (1988), the permanent or stationary income (or consumption), $\bar{y}_{jd}$, is determined only by the vector x_j, so that $\bar{y}_{jd} = E_d\lfloor y_{jd}\rfloor = \vartheta(x_j)$.

Nonetheless, we can assume that the equivalent income is determined by a dynamic process in the form:

$$y_{jd} = bx_j + \varphi y_{jd-1} + v\varepsilon_{jd-1} + \varepsilon_{jd}, \tag{1}$$

where *b* is the vector of coefficients related to x_j, φ is an autoregressive parameter, *v* is a moving-average parameter, and ε_{jd} is an error with mean zero. The autoregressive and moving-average parameters are included in the equation because we consider that income is conditioned by not only static determinants but also dynamic determinants.

In that way, if the expected income is given by $E_d\lfloor y_{jd}\rfloor = bx_j + \varphi y_{jd-1} + v\varepsilon_{jd-1}$ in time *d*, the stationary income in this period will be:

$$\bar{y}_{jd} = (1-\varphi)^{-1}(bx_j + v\varepsilon_{jd-1}). \tag{2}$$

Based on equation (1), poverty observed in time *d*, P_{jd}, can be evaluated as:

$$P_{jd} = p(y_{jd}) = p(\bar{y}_{jd} + \tilde{y}_{jd}), \tag{3}$$

where $p(.)$ is a poverty function and $\tilde{y}_{jd} = \varphi\left(y_{jd-1} - (1-\varphi)^{-1}(bx_j + v\varepsilon_{jd-1})\right) + \varepsilon_{jd}$ is the transient income resulting from the difference between the observed income and the stationary or permanent income in period *d*.

The chronic poverty measure is defined by the component C_{jd} of observed poverty, P_{jd}, which is a function only of permanent income, as follows:

$$C_{jd} = p(\bar{y}_{jd}) = p\left((1-\varphi)^{-1}(bx_j + v\varepsilon_{jd-1})\right). \tag{4}$$

Contrary to Jalan and Ravallion's approach (1998, 2000), this measure is also determined by a past shock, ε_{jd-1}, which establishes a state dependence for the chronic component of poverty. The assumption is that the *j*-person adjusts the expectation of long-run income after each shock, and this adjustment affects the chronic poverty level. That is, a hysteresis effect on chronic poverty is assumed.

Without shocks in period *d*, that is, $y_{jd} = \bar{y}_{jd}$, the observed poverty level must be equal to the chronic poverty measure. Otherwise, there is a residual component attributable to the difference between P_{jd} and C_{jd}. This component is defined as the transient poverty measure,

$$T_{jd} = P_{jd} - C_{jd} = p(\bar{y}_{jd} + \tilde{y}_{jd}) - p(\bar{y}_{jd}). \tag{5}$$

According to Cruces (2005), the use of T-C assessment accords with the literature on risk aversion, which states that individuals find it preferable to be in a stable income state rather than being subject to fluctuations around the same average income. The connection between the transitions from or to poverty and the household's risk of poverty is straightforward, since the latter is exactly due to income fluctuation. Therefore, the average transient poverty measure can be considered as an *ex-post* assessment of the household's vulnerability. The understanding of values in equation (5) can be summarized by the three following situations:

1. $T_{jd} > 0$, if there are well-being losses due to negative income shocks;
2. $T_{jd} = 0$, if there is no loss due to the variability of income;
3. $T_{jd} < 0$, if there are transient gains due to positive income shocks.

If there is no information on past individual income, y_{jd-1}, a substitute for calculating equations (4) and (5) can be a past poverty index, P_{jd-1}. Since poverty is assessed by some FGT index, the current expected poverty can be written as:

$$E_d[P_{jd}] = s_{jd} P_{jd-1} + e_{jd}(1 - P_{jd-1}). \tag{6}$$

where $s_{jd} = E[P_{jd} \mid P_{jd-1}]$ is the persistence rate of poverty and $s_{jd} = E[P_{jd} \mid 1 - P_{jd-1}]$ is the downward mobility rate of poverty. The downward mobility rate is the proportion of individuals who were non-poor in *t*-1 and became poor in *t*. But this concept should not be confused with transient poverty.

Expression (6) characterizes a Markov process. According to Boskin and Nold (1975), if we know rates s_{jd} and e_{jd}, we can calculate the stationary condition of this process. Then, in a stationary condition, the propensity to poverty that represents a chronic poverty status is given by:

$$C_{jd} = \frac{e_{jd}}{1 - s_{jd} + e_{jd}}. \tag{7}$$

Given that $P_{jd} = C_{jd} + T_{jd}$, the transient component of poverty in period *d* is defined as:

$$T_{jd} = p(y_{jd}) - \frac{e_{jd}}{1 - s_{jd} + e_{jd}}. \tag{8}$$

Since we are working with a headcount index (P0), it is possible to calculate the T-C components of current poverty estimating mobility rates s_{jd} and e_{jd}. The empirical model used to calculate these rates is presented in the next section.

4.2 EMPIRICAL MODEL

To estimate the determinants of the Markov process expressed in Equation (6), we have adopted a model similar to that proposed by Cappellari and Jenkins (2002, 2004). In this model, poverty mobility between two consecutive periods ($d-1$ and *d*) is analyzed by a bivariate model that is estimated in three steps: (i) the determination of the poverty status in period $d-1$ (initial condition); (ii) the determination of the poverty status in period *d*; and (iii) the correlation between non-observable effects that influence mobility or transition from one state to another. Presented below are the three components that, in combination, determine the mobility rates, s_{jd} and e_{jd}, of Equations (6), (7) and (8).

In the initial period, $d-1$, it can be assumed that the *j*-person is characterized by the latent propensity to poverty P^{*}_{jd-1} in the following form:

$$P^{*}_{jd-1} = z'_j\beta + \mu_{d-1} + u_{jd-1} \tag{9}$$

where z_j is a vector of explanatory variables that describe the *j*-person, β is a vector of parameters, μ_{d-1} is the coefficient of conjunctural effects, and u_{jd-1} is an error term that has a normal distribution with a mean of zero.

The function for the latent propensity to poverty, P^{*}_{jd}, that is, the status of poverty in period *d* conditional on the poverty in period $d-1$, can be characterized as a switching model, as follows:

$$P^{*}_{jd} = P_{jd-1}\left(x'_j\gamma_1 + \omega_{1,d-1}\right) + \left(1 - P_{jd-1}\right)\left(x'_j\gamma_2 + \omega_{2,d-1}\right) + u_{jd}, \tag{10}$$

where x_j is a vector of variables, γ_1 and γ_2 are vectors of coefficients, and $\omega_{1,d-1}$ and $\omega_{2,d-1}$ represent the conjunctural effects.

As long as Equation (10) refers to the poverty status that is conditional on lagged poverty, the error term in this equation can be correlated to the error term in Equation (9). According to Maddala (1983), it is assumed that the joint distribution of error terms, u_{jd-1} and u_{jd}, is bivariate normal and is characterized by a correlation that can be estimated. Taking such assumptions into account, this correlation is described in the following form: $\rho = \mathrm{corr}\left(u_{jd-1}, u_{jd}\right)$. If $\rho = 0$, there would be no problem of initial condition in the model: the status of poverty in $d-1$ would be treated as exogenous and the poverty transition equations could be estimated using univariate models. In other words, depending on the assumption of the existence or non-existence of a correlation between the two disturbances, the analysis of Equation (10) can be conducted through either an endogenous or an exogenous switching model.

It is important to emphasize that in the presence of two endogenous variables, that is, with $\rho \neq 0$, there is an identification problem in the model. In order to avoid this problem, some of the variables that may affect the initial condition of poverty should have no effect on mobility. Consequently, there should be variables belonging to vector z_j that are not included in vector x_j. Namely, they should be instrumental variables.

In order to estimate Equation (10), an observed persistent level of poverty in *d*, Per_{jd}, is defined as the minimum poverty level between two subsequent periods:

$$Per_{jd} = \min(P_{jd-1}, P_{jd}).$$

Meanwhile, an observed downward mobility in *d*, $Tran_{jd}$, is characterized by the increase in poverty from P_{jd-1} to P_{jd}:

$$Tran_{jd} = \max(0, P_{jd} - P_{jd-1}).$$

Or simply: $Tran_{jd} = P_{jd} - Per_{jd}$.

Thus, the dynamics between the poverty and the non-poverty states are given by the set of equations that characterizes the bivariate probabilities, $\alpha_k \in [0,1]$, of four distinct regimes in a Markov matrix:

period	D		
	state	Poor	not poor
$d-1$	poor	α_1	α_2
	not poor	α_3	α_4

where $\sum_k \alpha_k = 1$. The probabilities of each regime *k* are represented as follows:

$$\begin{aligned}
\alpha_1 &= E[Per_{jd} \mid z_j, x_j, d-1] = \Phi_2(z_j'\beta + \mu_{d-1}, x_j'\gamma_1 + \omega_{1,d-1}; \rho) \\
\alpha_2 &= E[P_{jd-1} - Per_{jd} \mid z_j, x_j, d-1] = \Phi_2(z_j'\beta + \mu_{d-1}, -x_j'\gamma_1 - \omega_{1,d-1}; -\rho) \\
\alpha_3 &= E[Tran_{jd} \mid z_j, x_j, d-1] = \Phi_2(-z_j'\beta - \mu_{d-1}, x_j'\gamma_2 + \omega_{2,d-1}; -\rho) \\
\alpha_4 &= E[1 - P_{jd-1} - Tran_{jd} \mid z_j, x_j, d-1] = \Phi_2(-z_j'\beta - \mu_{d-1}, -x_j'\gamma_2 - \omega_{2,d-1}; \rho),
\end{aligned} \tag{11}$$

where $\Phi_2(.)$ is an accumulated bivariate probability function.

Thus, the rate or probability of poverty persistence conditional on P_{jd-1} in Equation (6) can be calculated as follows:

$$s_{jd} = \Pr[P_{jd} > 0 \mid P_{jd-1} = 1] = \frac{\Phi_2(z_j'\beta + \mu_{d-1}, x_j'\gamma_1 + \omega_{1,d-1}; \rho)}{\Phi(z_j'\beta + \mu_{d-1})}, \tag{12}$$

and the downward mobility rate can be calculated as follows:

$$e_{jd} = \Pr\left[P_{jd} > 0 \mid (1 - P_{jd-1}) = 1\right] = \frac{\Phi_2\left(-z_j'\beta - \mu_{d-1}, x_j'\gamma_2 + \omega_{2,d-1}; -\rho\right)}{\Phi\left(-z_j'\beta - \mu_{d-1}\right)} . \quad (13)$$

In this Markov model, chronic poverty, which is identified in Equation (7), depends not only on individual characteristics, represented by vectors z_j and x_j, but also on a state dependence component. This state dependence is pronounced when the probability to be poor in *d* is considerably higher among those who were poor, rather than non-poor, in $d-1$.

The difference between the permanence rate and the downward mobility rate indicates the degree to which state dependence determines the probability of remaining in poverty (Stewart and Swaffield, 1999). According to Arulampalam et al. (2000), it is possible to identify a Genuine State Dependence (GSD) in poverty if there are notable differences between the vectors of coefficients γ_1 and γ_2 in Equation (10). The computation of the indicators for Aggregate State Dependence (ASD) and Genuine State Dependence (GSD) are shown in Appendix I. In Section 2 we gave an explanation of GSD and ASD. Here, we concentrate on explaining how they are measured and tested empirically. In the Appendix we present more details.

4.3 ESTIMATION METHOD FOR PSEUDO-PANEL DATA

Dynamic analysis of poverty normally requires longitudinal data in order to distinguish the chronic component of poverty from the transient component. However, surveys organized in panel format are scarce in many countries, including Brazil. For this reason, McKay and Lawson (2002) describe some alternatives for overcoming this difficulty. They claim that it is possible to differentiate these two components using 'dynamic information' from static data or repeated household surveys, as long as certain assumptions are made and the limitations of this approach are duly recognized.

One alternative is to analyze the magnitude of poverty experienced by different social groups in a 'pseudo-panel' format (Deaton, 1985; Verbeek and Nijman, 1992). These groups, assumed to be homogeneous, can be obtained when cohorts or subgroups of the population are aggregated by factors such as geographic location, sex or race. The advantage of this method is that it can estimate any changes that occur in these homogenous groups with greater precision than for individuals in panel analyses. In a pseudo-panel analysis, there is no problem of attrition bias since the same cohort is always observed, and information for the cohort is an average. This also minimizes measurement error. The disadvantage is that this method does not make any assessments of intra-group dynamics, so it cannot recognize the distinction between chronic poverty and transient poverty within each cohort.

In the pseudo-panel constructed for this study, poverty is given by the average index for individuals in each cohort. If poverty of cohort *j* were assessed, for example, by its average income, $\bar{y}_j = \sum_{ij=1}^{I_j} y_{ij} \Big/ I_j$, the probability of poor people being hidden within the cohort could be ignored when this average is sufficiently high. Thus, we choose explicitly to use an average poverty index as the dependent variable. Both average income and the average poverty index reduce our sample size. This is not a problem since we have a sufficient number of cohorts. In addition, the statistics are weighted by the cohort size. This estimated variable is the poverty headcount of each cohort *j*: $P_j = \sum_{ij=1}^{I_j} P_{ij} \Big/ I_j$, where $P_{ij} \in \{0,1\}$.

If the dependent variable, P_j , is a proportion of the poor, with $P_{ij} = 1$ for I_j individuals, it is possible to use a probit regression, considering that all members of the cohort have the same vector of characteristics $\mathbf{x}_j$. Accordingly, an observation is established as $\lfloor I_j, P_j, \mathbf{x}_j \rfloor$, $j = 1,..., J$. Then the population probability, $\pi_j = \Phi(\mathbf{x}'_j \boldsymbol{\beta})$, is estimated from the observed proportion P_j . In order to estimate consistently the Markov model in this approach, it is necessary to use a log-likelihood function that incorporates components of a bivariate distribution and to apply an endogenous switching model for the probit on grouped data. We seek to estimate the probability of poverty for those who were poor and those who were not poor in the past. But previous poverty is an endogenous condition. Thus, we choose to use the model described in Section 4.2, which has been adapted to grouped data. With the probabilities of each regime defined in Equation (11), the proposed likelihood function is represented by:

$$\ln L = \sum_{j=1}^{J} I_{jd-1} \begin{bmatrix} Per_{jd} \ln \alpha_1 + \left(P_{jd-1} - Per_{jd}\right) \ln \alpha_2 \\ + \left(Tran_{jd}\right) \ln \alpha_3 + \left(1 - P_{jd-1} - Tran_{jd}\right) \ln \alpha_4 \end{bmatrix}. \tag{14}$$

The estimators of $\gamma_1,\ \omega_{1d-1},\ \gamma_2,\ \omega_{2d-1},\ \beta,\ \mu_{d-1}$ and ρ of Equation (11) are obtained by maximizing the likelihood function. The techniques to maximize this function are both the Newton-Raphson algorithm and the Davidon-Fletcher-Powell algorithm. The marginal effects calculated from the estimated parameters are shown in Appendix II. In order to verify the existence of a correlation among the residuals, $\rho \neq 0$, a likelihood ratio test is conducted, assuming as a null hypothesis ρ equal to zero.

Although P_{jd} is observed for I_{jd} individuals, an equivalent number of individuals in *d* equal to I_{jd-1} is considered for the estimation of a proportional size. This equivalence assumption is needed so that Equations (9) and (10) are estimated with the same group size, I_{jd-1} . Another assumption of this estimation is that observed persistent poverty, Per_{jd} , and downward mobility, $Tran_{jd}$, are given by the gross transition rates of each cohort. That is, for each period, the mobility within a cohort is assumed to occur in just one direction. This implies that the results of this study should be interpreted mainly from the perspective of a cohort, not from the perspective of individuals.

In summary, Equation (10) is estimated by maximizing the likelihood function (14). Therefore, the coefficients that determine the persistent poverty, γ_1 and ω_{1d-1} , and the downward mobility, γ_2 and ω_{2d-1} , of cohorts are found on the basis of specifying the initial condition determined by Equation (9). The regression results are presented in Section 5.1. After estimating all of these coefficients, we calculate both the poverty persistence rate s_{jd} (Equation (12)) and the downward mobility rate e_{jd} (Equation (13)), as well as the level of chronic poverty C_{jd} of each cohort (Equation (7)).

4.4 DATA SOURCE AND COHORT DEFINITION

In order to analyze the dynamics of poverty, we chose the households surveys, PNADs (*Pesquisa Nacional por Amostra de Domicílios*), for 1993, 1995, 1997, 1999, 2001 and 2003 as the databases. Thus, five two-year transitions are analyzed for each cohort. Our mobility analysis could be affected by the choice of the beginning year, 1993, which was at the end of a highly volatile 'peak period' in Brazilian inequality (Ferreira et al., 2006). However, we can take neither a longer interval, due to the absence of data for earlier years, nor a shorter interval, since such an option would reduce the already small number of transitions.

In each period, the individuals living in urban areas[6] who were born in certain years (for example, 1945-1968, or who were, therefore, 35-58 years old in 2003), and had a certain observed household income[7] were selected. Within this sample, the household heads as well as their children, partners, other relatives and dependents have been examined. Only individuals who claimed to be guests, household employees or relatives of employees living within the household, according to the PNAD classification, were excluded from the analysis.

Based on this sample, cohorts have been constructed based on the use of individual characteristics such as: date of birth, race, sex, schooling level, and region of residence. These attributes were included because they are not likely to be altered during a two-year period.[8] Considering that, in each year, a sub-sample of at least 50 observations is representative for each cohort in PNAD, these groups were constructed according to the categories below:

- Birth date (3): people born between 1945 and 1952, between 1953 and 1960, or between 1961 and 1968;
- Race (2): whites (including Asians) or nonwhites (Browns, Blacks and Indians);
- Sex (2): male or female;
- Schooling (5): no education (0 or less than a year of formal education), incomplete elementary education (1-3 years of formal schooling), complete elementary education (4-7 years), complete middle education (8-10 years), or complete high school or higher (11 years or more);
- Region (3): residents in the South and Southeast regions, in the Central-West and North regions, or in the Northeast region.

In accordance with these categories, 180 cohorts have been constructed and analyzed during five transitions. This process has therefore generated a total of 900 observations, weighted by cohort size.

Owing to the identification problem in the model, which we have mentioned previously, it is also necessary to select an instrumental variable, which might affect an initial condition of poverty but does not have an effect thereafter on mobility. Heckman (1981) suggests that the initial condition can be analyzed through identifying idiosyncratic characteristics that are observed before the person enters the labour market. An example would be the socioeconomic conditions of the person's parents. Family background is an individual characteristic of adults in the sample. It is a proxy for the environment in which they grew up, so it is reasonable to consider that it affects only the starting point of the poverty dynamics during adulthood. In addition, very few adults continue to live with their parents, so parental characteristics are not likely to directly affect the current household conditions of those persons.

Thus, this study utilizes as an instrumental variable the average level of parental education of each cohort. The data were obtained from the PNAD of 1996, which reports information for this variable.[9] It is important to point out that this instrumental variable was selected only after comparing its impact with that of other variables that could have been included in the regression for the initial condition but not the regression for the transition.

Table 1 describes the sample average for the variables used in the model. As can be seen, about 20 per cent of the total sample is obtained from each year (1993, 1995, 1997, 1999 and 2001). The group born between 1961 and 1968 represents 41 per cent of the total; the group born between 1953 and 1960 represents 34 per cent; and the group born between 1945 and 1952 represents 24 per cent. Nonwhites account for 44 per cent of the total while whites account for 56 per cent. Women represent a majority of the sample, i.e., 52.7 per cent.

Those individuals in the sample who have completed elementary school represent 31.3 per cent and those who have completed high school 29.9 per cent. Individuals with no education represent 10.7 per cent while those having an incomplete elementary education account for 13.6 per cent. Lastly, those individuals with a completed middle-school education represent 14.8 per cent.

The South/Southeast region represents the largest group in the sample, namely, 55.3 per cent of the total. It is followed by the Northeast region, with 25.8 per cent, and the North/Central-West region, with 18.9 per cent. The instrumental variables related to the educational level of the parents of individuals are also shown in the third column of the table. Among other results, 36.1 per cent of the individuals' fathers and 42 per cent of their mothers had no education. These statistics emphasize the low level of education of parents for much of the sample.

TABLE 1

Descriptive statistics of the variables

Variable	Mean	Variable	Mean	Variable	Mean
d-1=1993	0.199	female	0.527	father with no educ.	0.361
d-1=1995	0.199	no education	0.107	father with incomplete element.	0.284
d-1=1997	0.200	incomp. elementary education	0.136	father with complete elementary	0.239
d-1=1999	0.194	comp. elementary education	0.313	father with middle school	0.046
d-1=2001	0.208	complete middle school	0.148	father with high school	0.069
born between 1961-1968	0.412	complete high school	0.299	mother with no educ.	0.420
born between 1953-1960	0.344	South and Southeast region	0.553	mother with incomp. element.	0.254
born between 1945-1952	0.244	Northeast region	0.258	mother with complete element.	0.225
nonwhite	0.443	North and Central-West region	0.189	mother with middle school	0.045
				mother with high school	0.057

Source: Own elaboration based on PNAD data.

5 RESULTS

In this section, we present the results obtained for our model, which was described in the previous sections. There are two subsections. The first reports on the results obtained from the regressions that we have described. The second subsection reports on the results of simulations, which were carried out on the basis of the initial results from regressions.

5.1 REGRESSION RESULTS

Table 2 shows the regression results of Equation (10), obtained using a relative poverty line of 60 per cent of median per capita household income. This table shows the marginal effects and the estimated coefficients of the covariates, along with their significance level, on the three conditions of poverty on which we focus: **the initial condition** (static), the **permanence of poverty** and the **transition into poverty.** In the Annex, Table A1 reports on the regressions estimated using other poverty definitions (e.g., using different poverty lines or definitions of equivalent income).

Our reference categories, dummies that are omitted from the regressions, are the year 2001 (d – 1); individuals born between 1945 and 1952; whites; men; individuals with complete high school or above; residents in the Central-West or North regions; and individuals whose parents have completed high school.

The parameter ρ represents the correlation of unobservable factors between the initial and subsequent conditions. In our exercise, we have found that this parameter is significantly negative. Such a sign indicates that idiosyncratic shocks, which are not explained by the observed variables but can lead people into poverty (or out of it), increase the probability, in this case, of leaving poverty (or being poor) in the next period.

Regarding the parameters for the initial condition (the probability of being in poverty or not), the marginal effects of the periods indicate that the propensity to poverty was considerably higher in 1993. This reveals that circumstantial non-observed factors were more 'perverse' in this year. For example, inflation was higher in 1993, which preceded the implementation of the '*Plano Real*'. Note that these period effects are not very sensitive to variations in the relative poverty line, but they are sensitive to changes in absolute poverty lines (see Table A1).

With regard to the probability of remaining in poverty, there is no distinction among the four initial periods. However, with regard to the last period, 2001, this probability increased by 15 percentage points among those who had previously been poor. Among those who were not poor, the marginal effects on the probability of downward mobility rose until 1997 but then decreased in 1999 and 2001. However, these values are very sensitive to changes in the definition of poverty.

When younger cohorts (born in 1953-60 or 1960-68) are compared to the older cohort (born in 1945-52), all of the coefficients were significantly positive and larger for the older group**.** This means that the older the cohort, the less likely its individuals are to be initially poor, to remain poor (if they were poor), and to fall into poverty (if they were not poor). However, considering that poor individuals have higher levels of mortality, older cohorts are likelier to be richer in aggregate simply because those among the cohort who were poor were more likely to have died.

The race covariate is significantly positive for explaining initial conditions and permanence conditions, but it does not help to account for downward mobility. Similarly, women are much more likely to be poor and to remain poor, yet they are less likely to fall into poverty. In other words, race and sex factors certainly play a role in keeping nonwhites and women in poverty. But the race effect does not play a major role in explaining how non-poor nonwhites could be downwardly mobile, and the gender effect inclines non-poor women to have a lower propensity to fall into poverty than men.

While the effect of education on initial conditions varies in accordance with the level of attainment, the differences in its effect on mobility can be separated into two major impacts. Cohorts who have completed middle school or a higher level are 15 percentage points less likely to remain poor than other educational groups. In addition, the probability of falling into poverty is five percentage points lower for cohorts who have completed elementary school or a higher level than for other cohorts.

As expected, we found that in the Northeast (NE) region, the unobserved effects on an initial condition of poverty and remaining poor are greater than in the other regions. It is well known that poverty is highly concentrated in this region. Nevertheless, the marginal effect of this regional category on downward mobility is very sensitive to changes in poverty definition (see Table A1). Thus, this effect does not differ from that of the North/ Central -West region, which was used as the base region in the regression. The South/Southeast (S and SE) region shows a negative effect on initial conditions and downward mobility when it is compared with the North/ Central-West region. However, individuals living in the South/Southeast are more likely to remain in poverty.

With regard to the relevant indicators for the Transient-Chronic (T-C) model, we find that 89 per cent of the poverty headcount during the period analyzed is attributable to a True or Genuine State Dependence (GSD), i.e., current poverty depends upon the past state of poverty after controlling for both observed and unobserved heterogeneities of individuals. As previously explained, the difference between the state dependence observed in the aggregate data, the so-called Aggregate State Dependence (ASD), and the Genuine State Dependence is the level of state dependence explained by individual heterogeneity. We can see that only four per cent of ASD is attributable to individual heterogeneity while the remaining 96 per cent is due to Genuine State Dependence. In other words, 96 per cent of the cohort stays poor because they were persistently poor in the past. Only four per cent stay poor due to their individual characteristics.

As we have pointed out earlier, if persistence derives from Genuine State Dependence, then the measures needed to lift households out of poverty during a certain period, such as an ambitious *Bolsa Família* programme, should also help reduce the future chances of these same households falling back into poverty. However, if persistence is caused by adverse characteristics of cohorts, such as features related to education, race, region (as well as non-observed characteristics), cash transfers could be inadequate since they are likely to have little direct impact on such characteristics.

When we use absolute instead of relative poverty lines (see Table A1), the impact of state dependence is reduced considerably. Such a result corroborates Yaqub (2003) by confirming that it is more difficult to reduce relative deprivation than absolute deprivation. Also, as expected, the higher the value of the relative poverty line, the greater the impact of state dependence.

TABLE 2

Regression results for a poverty line of 60% of the median per capita household income

(Robust Std. Err)	**Initial condition**			**Permanence in poverty**			**Transition to poverty**		
Covariates	**Marg effect**	Coef.	P>z	**Marg effect**	Coef.	P>z	**Marg effect**	Coef.	P>z
d-1=1993	**0.018851**	0.077934	0.000	**0.155759**	0.232352	0.000	**0.003795**	0.192178	0.000
d-1=1995	**0.008405**	0.035199	0.000	**0.149774**	0.392453	0.000	**0.007558**	0.333203	0.000
d-1=1997	**0.007378**	0.030939	0.000	**0.150021**	0.484468	0.000	**0.008777**	0.373412	0.000
d-1=1999	**0.009783**	0.040894	0.000	**0.148248**	0.205080	0.000	**0.003564**	0.181264	0.000
birth 1961-1968	**0.147327**	0.592759	0.000	**0.237628**	0.413539	0.000	**0.003980**	0.230896	0.000
birth 1953-1960	**0.073314**	0.296382	0.000	**0.187301**	0.089590	0.000	**0.000421**	0.035796	0.000
nonwhite	**0.016025**	0.067578	0.000	**0.147178**	0.100312	0.000	-0.000086	0.003693	0.242
Female	**0.012162**	0.051562	0.000	**0.141664**	-0.080036	0.000	**-0.001013**	-0.047945	0.000
no education	**0.004458**	0.018733	0.000	**0.140180**	-0.023261	0.000	**0.006392**	0.278604	0.000
incomplete elementary	**0.020010**	0.082173	0.000	0.153471	-0.001437	0.793	**0.005402**	0.249102	0.000
complete elementary	**0.009057**	0.038066	0.000	**0.145297**	0.141798	0.000	**-0.001177**	-0.059084	0.000
S and SE region	**-0.082197**	-0.341671	0.000	**0.104079**	0.083233	0.000	**-0.005833**	-0.298993	0.000
NE region	**0.094891**	0.368452	0.000	**0.209735**	0.101045	0.000	**-0.000057**	0.011860	0.001
constant	**-**	-3.230803	0.000	**-**	1.239791	0.000	-	-2.664327	0.000
Instrumental variables									
father with no educ.	**0.124290**	0.551496	0.000						
father incomp. elementary	**-0.136351**	-0.605012	0.000						
father comp. elementary	**-0.036498**	-0.161949	0.000						
father with middle school	**-0.364212**	-1.616069	0.000						
mother with no educ.	**0.611922**	2.715203	0.000						
mother incomp. element.	**0.342938**	1.521674	0.000						
mother comp. elementary	**0.396289**	1.758403	0.000						
mother with middle school	0.001794	0.007963	0.806						
ρ		-0.321840		p < 0.000					
Log likelihood		-210092.03		**Number of obs**		427658			
Wald chi2(29)		71972.36		p < 0.000					
GSD test chi2(13)		829.16		p < 0.000					
ASD		0.922346		**GSD**	0.888567	(0.0585)			
Predicted probabilities	**alfa1+alfa2**	0.205955	(0.1867)	**alfa1**	0.191822	(0.1789)	**alfa3**	0.007265	(0.0048)
Conditioned probabilities				**s**	0.899765	(0.0635)	**e**	0.011197	(0.0113)
Chronic poverty		0.146837	(0.1655)						
Observed poverty		0.201341	(0.1853)						

Source: Own elaboration based on PNAD data.

Finally, 73 per cent of total observed poverty from 1993 to 2003 (0.2013 in Table 2) is derived from a chronic condition, or a 'stationary' propensity to poverty (0.1468/0.2013) while the remaining 27 per cent is derived from transient poverty (0.0545/0.2013). When different poverty lines are compared, the deprivation with the highest chronic component is that of absolute indigence (82 per cent) while the other absolute poverty measures show percentages similar to those for the relative measures (Table A1).

5.2 THE MODEL'S PREDICTION

In order to analyze the differences between chronic poverty and transient poverty, we simulate predicted values for each individual within the cohorts according to coefficients estimated in our model described above. When comparing the five macro-regions in Brazil, as shown in Table 3, we note that the highest persistence rate (*s*) and downward mobility rate (*e*) are in the Northeast region, as well as the highest observed poverty, chronic poverty and transient poverty. Consequently, where social conditions are the worst in this region, the chance of upward mobility is also the lowest.

TABLE 3

Predicted values for individuals' conditioned probabilities and poverty by their region, education, race and sex

	Conditioned probabilities		Poverty			
	s	e	Observed	Chronic	Transient	Trans/Obs
Region						
Southeast	0.886042	0.005574	0.115211	0.074987	0.040223	0.3491
South	0.883308	0.005536	0.114300	0.071552	0.042748	0.3740
Northeast	0.932478	0.021454	0.407015	0.290789	0.116226	0.2856
Central-West-	0.896284	0.014958	0.171764	0.172823	-0.001059	-0.0062
North	0.902962	0.016082	0.307629	0.189867	0.117761	0.3828
Education						
no education	0.923615	0.025012	0.476701	0.286145	0.190557	0.3997
incomplete elementary	0.914135	0.017618	0.324938	0.217027	0.107912	0.3321
complete elementary	0.924598	0.006500	0.202526	0.123299	0.079227	0.3912
comp. middle school	0.865007	0.006741	0.069556	0.075308	-0.005752	-0.0827
Race/Sex						
nonwhite men	0.930886	0.014898	0.280198	0.218123	0.062075	0.2215
nonwhite women	0.923427	0.013744	0.319462	0.192499	0.126963	0.3974
white men	0.882867	0.007580	0.108306	0.090435	0.017871	0.1650
white women	0.871190	0.006903	0.121101	0.076873	0.044228	0.3652

Source: Own elaboration based on PNAD data.

With regard to the effects of the educational level, the persistence rate is similar among those who have not completed middle school but it is lower for those with higher formal education. With regard to the downward mobility rate, there are similar probabilities for the individuals whose educational level is above complete elementary education. As expected, observed, chronic and transient poverty show a negative correlation with educational level. However, as indicated by the statistics in the last column, the transient component of poverty is relatively more pronounced not only for those without formal education but also for those who have only completed elementary education. In these two groups, almost 40 per cent of the observed poverty derives from the transient component. These groups might be more inclined to periodic changes of their status in the labour market, and therefore are more vulnerable to changes in their state. Those who have completed middle school showed the lowest chronic poverty level, 7.5 per cent, and were less subject to fluctuations in income.

With regard to race, nonwhites exhibit the worst poverty indicators, regardless of sex. In contrast, the characteristics that differentiate men from women are similar across races. Men present higher persistence (*s*) and downward mobility (*e*) rates: as a result, they are more prone to chronic poverty than women. Observed poverty is higher for women than for men due to a large transient component (which is corroborated by the high percentages in the last column). Similar to the evaluation done by Rocha (2003), we can see that both sexes have similar results for observed poverty, with women having a slight disadvantage. However, our results suggest that the components of poverty are distinctly different for the sexes. This result might be due to the tenuous connection of women to the labour market.

Table 4 shows other simulations for individuals in specific types of households classified in accordance with their composition and the characteristics of their household head. It is important to emphasize the loss of information inherent in this analysis since these temporary aspects have not been followed over time. In general, in single-parent households without children (the second category), individuals have transient gains in well-being (suggested by the negative coefficients). This indicates that there might be a trade-off between marriage with children and being single without children. But individuals in households headed by a single female parent (4) are more vulnerable to transient deprivation than those in households headed by a single male parent (3). Since the participation of these female heads in the labour market is likely to be marked by discrimination and segregation, they are more susceptible to precarious occupations and unemployment.[10]

TABLE 4

Predicted values for individuals' conditioned probabilities and components of poverty in selected types of household

	Household head									
	White					Nonwhite				
	s	e	C	T	T/(C+T)	s	e	C	T	T/(C+T)
(1). Employed, no middle school, married, with children (0-10 years) in the household	0.9141	0.0093	0.1266	0.0647	0.3382	0.9382	0.0173	0.2493	0.1547	0.3829
(2). (1) not married and without children in the household	0.8953	0.0078	0.0966	-0.052	-1.1757	0.9271	0.0139	0.1960	-0.1030	-1.1053
(3). (2) male head with children in the household	0.9151	0.0107	0.1405	0.0507	0.2652	0.9387	0.0170	0.2483	0.1146	0.3158
(4). (2) female head with children in the household	0.9098	0.0092	0.1203	0.1692	0.5845	0.9373	0.0167	0.2405	0.2723	0.5310
(5). (1) with complete middle school	0.8656	0.0062	0.0654	-0.032	-0.9640	0.9105	0.0097	0.1379	-0.0260	-0.2269
(6). (1) unemployed	0.9027	0.0092	0.1177	0.3696	0.7585	0.9305	0.0161	0.2242	0.4321	0.6584
(7). (1) undocumented or job with no remuneration*	0.918	0.0118	0.1573	0.1777	0.5304	0.9416	0.0214	0.2961	0.2866	0.4918
(8). (1) self-employed	0.9123	0.0101	0.1335	0.0839	0.3859	0.9374	0.0191	0.2653	0.1754	0.3980
(9). (1) with private documented or public sector job	0.9142	0.0081	0.1137	0.0200	0.1496	0.9373	0.0141	0.2158	0.0764	0.2615
(10). (1) female head with paid domestic job	0.9056	0.0096	0.1224	0.0677	0.3561	0.9320	0.0142	0.2071	0.2134	0.5075

Note: * Does not include domestic jobs.

Source: Own elaboration based on PNAD data.

Simulations (1) and (5), when compared, show that the completion of middle school education by the household head reduces the probability of chronic poverty and generates significant transient gains. This result is similar to that regarding individual features analyzed in Table 3. The differences observed in the indicators reveal that education goes a long way in explaining not only the relative position of individuals in the income distribution, as suggested by Ferreira (2000), Ramos and Vieira (2000), and Menezes-Filho (2001), but also their mobility.

Unemployment is a condition more associated with vulnerability to poverty than with a chronic state of poverty, as can be noticed in a comparison between Simulations (1) and (6). Such a result is expected since unemployment is often a transient condition related to a short-term downturn of the economy. This leads one to believe, as shown by Ramos and Santana (1999), that the elimination of unemployment in the economy would have a modest effect on the reduction of structural poverty in Brazil.

The transient component explains around 40 and 50 per cent of observed poverty in households headed by self-employed workers and undocumented workers, respectively (see simulations (7) and (8)). This finding highlights the importance of implementing compensatory policies, such as some form of unemployment insurance, not only for formal workers but also for informal workers. As emphasized by Ferreira et al. (2000), designing such policies should take into account that recessions affect not just aggregate demand in general but also demand conditions in the informal labour market. Also note that the chronic component of poverty is greater in Simulations (7) and (8) than in most of the others. These two phenomena, chronic poverty and informal insertion into the labour market, can be linked through a process of circular causality. That is, chronically poor workers are likely to be more inclined to pursue so-called survival strategies (such as securing temporary or undocumented jobs) that would increase their vulnerability to transient shocks. In turn, the resultant precarious position of these workers in the labour market can reduce their well-being in the long run, i.e., make them more prone to permanent poverty.

The results for female domestic workers (Simulation (10)) show that their position is slightly better than those described for self-employed or undocumented workers with regard to both chronic poverty and transient poverty. Nevertheless, for a household with a nonwhite woman as its head, the transient component has greater importance than the chronic component.

Finally, the persistence rate of individuals in households headed by nonwhites is remarkably stable. That is, in comparison to other features, the race effect stands out as a major determinant of the persistence of poverty. Henriques (2001) also showed, for example, that black people are over-represented in Brazilian poverty and face a persistent disadvantage in relation to white people. He also pointed out that in the last decade this discriminated group has not been improving its average well-being faster than the rest of the population thus remaining in the same relative position.

6 CONCLUSION

This Working Paper has tried to demonstrate the value of an estimation method, based on a Markov model and the use of aggregate information, for analyzing poverty as a dynamic phenomenon. This model permits analysts to examine the determinants of permanence in poverty and transition to poverty for samples of population cohorts. The paper also demonstrates how to use the predicted values of this model to decompose poverty into two major components (chronic and transient).

However, as we pointed out above, this method has limitations. The length of the transition interval, namely, two years, and the aggregation of individual information into homogenous groups lead to the neglect of intra-period and intra-group dynamics. For individuals, such aggregation might lead to an over-estimation of the persistence rate and an under-estimation of the downward mobility rate. In any case, this approach has the advantage of capturing medium- and long-term tendencies more effectively. Furthermore, it is better able to contextualize poverty as a group phenomenon, rather than just as an individual phenomenon. Since the availability of pseudo-panels is larger than that of panel data, future research can use this proposed method to analyze chronic and transient poverty in a larger number of countries.

The results of our regressions show that the most recent period analyzed (from 2001 to 2003) had the most favourable conjunctural effects for reducing relative poverty. But they also show that younger cohorts tended to exhibit more downward mobility into poverty. Race and sex were found to be determining factors in keeping nonwhites and women in poverty. However, being nonwhite or female does not increase one's chances of falling into poverty. With regard to educational factors, our results show that an elementary school diploma reduces the probability of cohorts falling into poverty while a middle school diploma reduces the chances of their staying in poverty. The differences among other educational levels were not important, however.

During the whole period analyzed (1993-2003), we find that 73 per cent of relative poverty in Brazil was chronic. This high proportion of chronic poverty is due mainly to the effect of state dependence. In fact, 89 per cent of the observed poverty headcount was due to a Genuine State Dependence. That is, poor people remained in poverty overwhelmingly because they were persistently poor in the past, independently of their personal characteristics. These results are robust to changes in the poverty threshold, except for the use of the threshold for indigence.

As suggested, in general terms, by the Chronic Poverty Report 2004-05 (CPRC, 2004), the findings of our own study demonstrate that the individuals most susceptible to chronic poverty are nonwhites, the least educated, and the residents in the Northeast region of Brazil. We found that nonwhites were over-represented in chronic poverty virtually independently of any other features. According to our estimates of mobility rates, individuals in the Northeast region face not only the worst social conditions but also have the lowest chance of upward mobility. It might be interesting for further research to estimate region-specific models since the poverty profile in the Northeast differs markedly from those in other regions.

Another group that was identified by our modelling as unduly inclined to chronic poverty was households headed by self-employed or unregistered workers. This finding suggests that chronic poverty is correlated with informal occupation. This occupational condition also reinforces the overall vulnerability of such groups to transient shocks.

In general, observed, chronic and transient poverty are negatively correlated with educational level, as one would expect. However, the transient component of poverty was found to be more pronounced for poor individuals who either had achieved only an elementary education or had no formal education. The explanation is that these groups are probably more influenced by cyclical changes in the labour market and, therefore, more vulnerable to shocks than those with completed middle education.

Our findings for men and women show distinctly different patterns. Probably due to the precarious character of female participation in the labour market, women's poverty has a larger transient component than men's. Also, people living in a single-parent household headed by a woman are also more prone to transient poverty. Similarly, the results obtained for households headed by an unemployed person emphasizes that the reduction of unemployment will have only a modest effect on structural poverty.

We believe that the analysis of poverty as a dynamic phenomenon can help policymakers design more effective anti-poverty policies. For example, those groups more prone to chronic poverty would require a more systematic, multi-sectoral approach that helps break the inter-generational transmission of poverty. An alternative that we propose considering for reducing chronic poverty is a large programme of income redistribution, such as proposed by Gaiha and Deolalikar (1993). However, those groups more affected by transient poverty could be helped by providing them with greater access, or more secure access, to employment opportunities. This could involve implementing special income generation programmes or more efficient forms of social protection.

Since Brazilian poverty is essentially chronic and is due mainly to a path dependence effect, an effective policy of reducing poverty should involve both a systematic multi-sectoral approach and an extensive programme of income redistribution. Programmes that seek to improve human capital and access to public services, as well as enhance their quality, are needed. But they should be combined with programmes explicitly designed to reduce income inequality. The reason is that deprivation of income is a condition that postpones or weakens the potential impact of policies, such as promoting education or health, that are designed to improve the capabilities of poor people.