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Do Changes in the Labour Market Take Families Out of Poverty? Determinants of Exiting Poverty in Brazilian Metropolitan Regions

Ana Flavia Machado [a] & Rafael Perez Ribas [b]
[a] Federal University of Minas Gerais , Brazil
[b] International Poverty Centre/UNDP , Brazil
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Do Changes in the Labour Market Take Families Out of Poverty? Determinants of Exiting Poverty in Brazilian Metropolitan Regions

ANA FLAVIA MACHADO* & RAFAEL PEREZ RIBAS**
*Federal University of Minas Gerais, Brazil, **International Poverty Centre/UNDP, Brazil

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ABSTRACT *Using survival models, we test whether short-term changes in the labour market affect poverty duration. Data are from the Brazilian Monthly Employment Survey. Such a monthly dataset permits more accurate estimations of events than using annual data, but its panel follows households for a short period. Then methods that control for both right- and left-censoring should be used. The results are as follows: households with zero income are not those with the lowest chances of exiting; changes in aggregate unemployment do not affect poverty duration; and increasing wages in the informal sector has a negative effect on poverty duration.*

I. Introduction

The reasons that a family remains in poverty may be associated not only with its idiosyncratic features but also with characteristics of the environment where it lives (Adato et al., 2006; Carter and Barrett, 2006; Hoddinott, 2006). On the supply side, household characteristics are the critical determinants of leaving poverty. However, on the demand side, we are interested in discovering whether changes in the labour market, such as fluctuations in the unemployment rate and the average wage, have any effect on the duration of households in poverty.

This paper aims to test whether changes in aggregate demand are capable of removing households from poverty. In Brazil, there is a household panel that allows carrying out this kind of analysis: the Monthly Employment Survey (PME, *Pesquisa Mensal de Emprego*). The PME is one of a few surveys that have the advantage of being a monthly panel, so it allows a more accurate estimate of the relationship between events and poverty dynamics than annual panel surveys. The reason is that

Correspondence Address: Ana Flavia Machado, Federal University of Minas Gerais, Department of Economics, Avenue Antônio Carlos, 6627, Belo Horizonte, 31270-901 Brazil.
Email: afmachad@cedeplar.ufmg.br

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associating an annual change with an event that took place at some moment within 12 months is more difficult than associating a monthly change with an event that took place in that same month.

In addition, we intend to estimate other determinants of this transition, taking into account the length of time that they have been in poverty. For this reason, our study adopts survival models to estimate the determinants of poverty exit. Many studies have shown that the longer one remains in poverty, the greater are the chances of permanence in that condition (Iceland, 1997b; Stevens, 1999; McKernan and Ratcliffe, 2003; Adato et al., 2006; Carter and Barrett, 2006; Barrett et al., 2006). However, some of them have used panels with only two or three waves, so they have been forced to implement probit (or logit) models which do not assess the duration effect accurately, for example, Krishna et al. (2006).

Unfortunately, the period of 16 months between the first interview and the last one in the PME is not enough to estimate the length of time that one remains in poverty. It results in a high number of both right-censored, when it is not observed households moving out of poverty, and left-censored observations, when the entry of households into poverty is not observed. In order to reduce the bias generated by censoring, we make use of survival models considering left-censoring as a problem of initial condition.

II. Duration In and Mobility Out of Poverty: a Brief Review of the Literature

Baulch and Hoddinott (2000) state that there are three dimensions for analysis of economic mobility and poverty dynamics: metric, temporal, and methodological. Estimations on duration of poverty take into account the temporal dimension. However, this kind of study is more common in developed countries, where more longitudinal data are available. The majority of studies have been conducted in the USA, based on the Panel Study of Income Dynamics (PSID). The examples are Duncan (1983), Bane and Ellwood (1986), Ruggles and Williams (1987), Duncan and Rodgers (1991), Stevens (1994, 1999), and McKernan and Ratcliffe (2003).

One conclusion of these studies is that the omission of censored data may underestimate the average time spent in poverty (Bane and Ellwood, 1986; Stevens, 1994, 1999). However, analysis based on multiple spells of duration is only possible when there is a panel with a large number of waves. Another conclusion is that analysis of duration using annual data ignores a series of events that occur between the two interviews (Ruggles and Williams, 1987; Iceland, 2003; McKernan and Ratcliffe, 2003).

The study made by Iceland (1997b) also uses the PSID to estimate the chances of leaving poverty. He attempts to relate aspects of aggregate demand to this event by using covariates that express changes in the US urban labour market from 1970 to 1985. His results indicate that spatial segregation of economic activity does not produce any significant effect on moving out of poverty. Nevertheless, urban de-industrialisation tends to favour Whites more than Blacks with regard to transitions out of poverty.

In other countries, studies on poverty dynamics include those made by Hussain (2002) in Denmark, Cappellari and Jenkins (2002) in the UK, Beccaria and Maurízio

(2006) in Argentina, Dmitri (2000) and Denisova (2007) in Russia, and Bigsten and Shimeles (2003) in Ethiopia. The results generally indicate that the event of entry into poverty and permanence in this state are associated more with changes related to employment than with household structure and composition. Nevertheless, most of the studies estimate only the effect of changes in individual labour condition and do not consider the endogeneity of these changes in relation to income mobility. One way of estimating the effect of employment on poverty dynamics is to use macro variables that assess exogenous changes in the labour market.

In Brazil, there are a few studies of poverty duration. The study by Barros, Mendonça and Neri (1995) was one of the first to investigate this topic. They also used the PME panel, but they made only a descriptive analysis. Their analysis intended neither to investigate the determinants of poverty spells nor control for the problem of censoring. Other studies are those carried out by Machado et al. (2007) and Ribas and Machado (2007). Both studies concluded that being in the informal sector has an ambiguous effect on mobility because it contributes to both exiting poverty and increasing the vulnerability to poverty.

III. Data

The PME is a rotating panel that observes the same household for four consecutive months and, after an eight-month interval, observes it consecutively for four more months. After a total of eight interviews in a 16-month interval, the household leaves the sample permanently. Moreover, it is representative of six Brazilian metropolitan regions: Recife, Salvador, Belo Horizonte, Rio de Janeiro, São Paulo and Porto Alegre. Besides its microdata at household level, the PME provides monthly statistics on the labour market in these six regions.

Imputation of Non-labour Income in the PME

As a result of its specific interest in investigating the urban Brazilian labour market, the PME provides information only about income from work. For this reason, we have adapted the technique proposed by Elbers et al. (2003) to impute non-labour earnings to the households surveyed by PME by using data from the Brazilian National Household Survey (PNAD).

In order to attribute non-labour income to households in the PME, we estimated a model for each type of income using the PNAD. These models were estimated based on Heckman's (1979) two-step method. In the first step, we estimated the probability of receiving a particular type of non-labour income using a probit model. In the second step, we estimated the values of earnings according to a subset of variables from the first step and the inverse of the Mill's ratio. The covariates in both the first and the second steps were selected by using a stepwise estimation. Therefore, 96 equations were estimated (combining four income sources, six metropolitan regions and four years, from 2002 to 2005).

Once the probability of receiving sources of non-labour income and their amounts had been estimated, the coefficients and standard errors, assumed heteroskedastic, were exported to the PME data. Further details about the process of imputation can be found in Ribas and Machado (2008).

Sample and Description of Variables

The data on poverty duration are taken from the PME that was conducted from March 2002 to May 2007. We took the poverty line for metropolitan regions calculated by the World Bank (2006) and deflated for the months in the PME.[1] Then, we classified as 'poor' households the ones whose per capita income was below this line.

In order to produce the database used specifically to analyse poverty duration, we used, first of all, the algorithm proposed by Ribas and Soares (2008) to put together the whole panel of individuals. Then, we identified those households in which at least one member was observed in more than one interview and separated them from those households in which all the members had left the sample. In other words, we considered a household to have undergone attrition when none of its members were observed subsequently in the sample.

Once the families that had been interviewed at least twice and had spent no less than one month in poverty had been identified, we counted the number of months each family had been in this state. This period was calculated according to the number of months between two consecutive observations. For instance, in the case of the household that had already fallen into poverty at the time of the fourth interview, remained in the same treated situation for the fifth interview (eight months afterwards) and had exited poverty by the time of the sixth interview, we assumed that it had been in deprivation for 10 months. This same criterion of interpolation of periods was adopted for households whose attrition had occurred in a particular month of an interview, but had recovered one month later.

However, if this household had been observed to be out of poverty at the time of the fifth interview, we treated it as right-censored, because we did not know in what month it had actually left poverty. Figure 1 shows five examples of how observations in the panel are handled in terms of poverty spells.

Table 1 presents the descriptive statistics for the selected variables used in the poverty duration model and shows that the average observed duration in poverty was 2.69 months. However, almost 45 per cent of the sample is right-censored, while about 46 per cent is left-censored. In addition, the average income gap for poor households is 51 per cent of the poverty line.

Table 2 shows the size of the samples used in the estimates of the duration models. In the reduced sample, used to calculate just the effects of fixed variables, there is a similar number of observations that are only right-censored or only left-censored (approximately 30%), while 16 per cent of the data are interval-censored. Based on these statistics, we concluded that the relative number and, most importantly, the absolute number of observations *not* censored are sufficient to estimate the effects of a poverty duration model using the PME data. In the expanded (split) sample, used to estimate the effects of fluctuations in aggregate demand, the number of right- and interval-censored observations increased and, as a result, the percentage of non-censored cases was reduced. Nonetheless, there was only a slight reduction in the absolute number of these cases.

The difference between the reduced sample and the split sample lies in the number of times that the same household appears in the database. In the first case, each household is represented by only one observation, which contains the total number

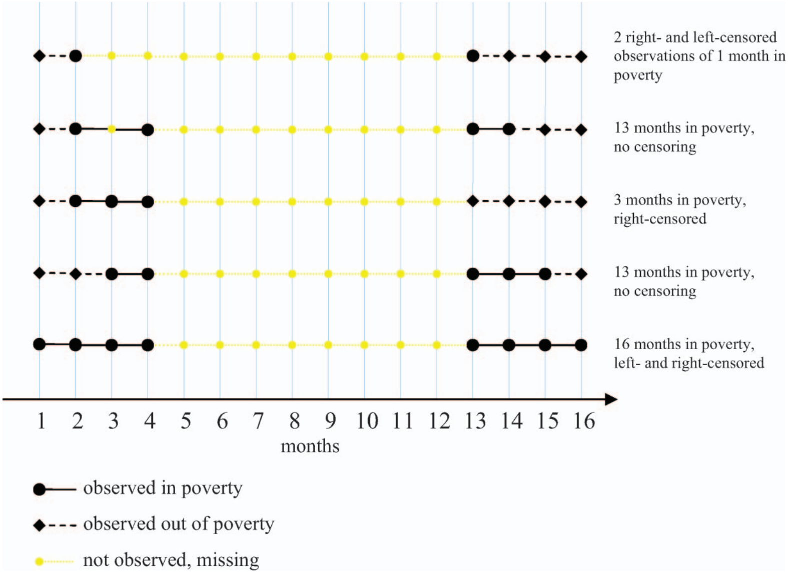

Figure 1. Examples of poverty spells in the Monthly Employment Survey (PME) panel.

of months that it was in poverty, censored or not, and the fixed variables that permanently characterise it. These fixed variables are generally those that represent the household's characteristics at the first time that it was observed in poverty. In the second case, each observation corresponds to a month that the household was in poverty. In other words, the same household can be repeatedly reported in the split sample.

IV. Empirical Framework: Survival Models

In regression analysis, we exclude neither the right-censored cases (when the movement of households out of poverty was not observed) nor the left-censored cases (when the entry of households into poverty was not observed). In the former case, the use of conventional survival models provides a method to treat this problem. But the latter case is not so simple because a left-censored sample can introduce bias into the analysis. Moreover, the omission of such data provides a stronger bias than their inclusion because it would systematically exclude people who are in the midst of a long period of poverty (Iceland, 1997a).

In order to reduce this possible bias, we make use of survival models taking into account the probability of moving into poverty. Thus we consider left-censoring as a problem of initial condition (Ridder, 1984). These models, however, are based on a stationarity assumption, that is, the conditional probability of moving into poverty is assumed to be constant (D'Addio and Rosholm, 2002).

The well-known survival models are the most suitable for estimating the time that a household is likely to spend in poverty. The so-called 'failure' takes place when the process of moving out of that condition occurs. Using these models, one can estimate the probability of remaining in poverty beyond a specific period of time t, called

Table 1. Descriptive statistics of the variables

Variable	Mean	Standard deviation
Observed duration	2.69268	0.011981
Right censoring	0.44832	0.001637
Left censoring	0.46455	0.002313
MA Recife	0.11748	0.000854
MA Salvador	0.09659	0.000703
MA Belo Horizonte	0.10125	0.000563
MA Rio de Janeiro	0.22308	0.001090
MA São Paulo	0.38088	0.001414
MA Porto Alegre	0.08072	0.000483
Poverty income gap	0.51138	0.001115
Poverty income gap squared	0.39594	0.001281
Log of number of members	1.10952	0.001921
Extended household	0.05669	0.000640
Proportion of working-age members	0.58794	0.000871
White head	0.45204	0.001588
Number of strata	372	
Number of PSU	80432	
Unmarried head	0.45482	0.001510
Unmarried female head	0.37072	0.001449
Head's age	46.3144	0.049177
Presence of:		
one child or more	0.46791	0.001572
two children or more	0.21964	0.001296
one adolescent or more	0.30931	0.001380
two adolescents or more	0.20069	0.001153
one elderly person or more	0.16691	0.001152
illiterate adult	0.15381	0.001054
functionally illiterate adult	0.35967	0.001448
adult with elementary school	0.56801	0.001505
at least two adults with elementary school	0.23310	0.001259
adult with high school	0.32480	0.001450
adult with college education	0.03195	0.000572
Number of observations	165656	
Universe of households	6.90E+07	

Note: MA = Metropolitan Area; PSU = Primary Sample Unit.
Source: Own calculations based on the Monthly Employment Survey (PME) 2002–2007.

the survival function. It can be expressed as $S(t) = P(T \geq t)$ or $S(t) = 1 - F(t)$, where $F(t)$ represents the accumulated distribution of cases from the time zero to the time t.

The probability of a failure taking place, which is also called the hazard function or rate, can be described on the basis of the difference between the survival function at two moments, $S(t_1) - S(t_2)$ weighted by the length of that interval:

$$h(t) = \frac{S(t_1) - S(t_2)}{(t_2 - t_1)S(t_2)}.$$

Table 2. Number of observations

Reduced sample		
Total observations	165,656	Per cent
Non-censored	40,548	24.48
Right-censored	48,653	29.37
Left-censored	49,618	29.95
Interval-censored	26,837	16.20
Expanded (split) sample		
Total observations	324,056	Per cent
Non-censored	40,036	12.35
Right-censored	94,796	29.25
Left-censored	47,227	14.57
Interval-censored	141,997	43.82

Source: Own calculations based on the Monthly Employment Survey (PME) 2002–2007.

Also, if $f(t)$ represents the density function of cases according to survival time, the hazard function can be expressed as:

$$h(t) = \frac{f(t)}{S(t)} = \frac{f(t)}{1 - F(t)},$$

bearing in mind that $F(t) = \int_0^t f(s)ds$.

In parametric models, the function $f(t|X)$ can take on various forms. Unfortunately, due to the large number of left-censored cases, we were unable to carry out tests of adequacy of distributions, such as the Cox-Snell test, in order to find out which of them is the most appropriate. Therefore, we decided to estimate models that are based on different distributions in order to check the robustness of our results. The density functions for each of the assumed distributions are described below:

$$\begin{array}{ll} f(t \mid X) = \gamma\lambda t^{\gamma-1} \exp\left(-\lambda t^{\gamma}\right) & \text{Weibull} \\ f(t \mid X) = \lambda \exp\left(\gamma t - \lambda\gamma^{-1}(e^{\gamma t} - 1)\right) & \text{Gompertz} \\ f(t \mid X) = \dfrac{\mu^{1/\gamma} t^{1/\gamma - 1}}{\gamma\left(1 + (\mu \cdot t)^{1/\gamma}\right)^2} & \text{Log-logistic} \\ f(t \mid X) = \dfrac{1}{\sqrt{2\pi\gamma \cdot t^3}} \exp\left[-\dfrac{(t-\lambda)^2}{2\gamma\lambda^2 t}\right] & \text{Inverse Gaussian,} \end{array} \tag{1}$$

where, $\lambda = \exp(X'\beta)$, $\mu = \exp(-X'\beta)$ and γ and β are parameters that define the format of the conditional distribution.[2]

The inverse Gaussian distribution, parameterised according to the Wiener process with absorption (namely, the process starts at some positive value and finishes whenever it hits zero) was also used in this paper. Wiener processes are normally used to calculate the distance between the beginning of the process and the state of absorption (Lancaster, 1982; Doksum and Høyland, 1992). Thus, it is assumed that the process of falling into poverty is heterogeneous and that distance determines the format of the hazard function. According to Aalen and Gjessing (2001), a long distance between the two points is associated with a rising hazard rate.

An intermediate distance implies a hazard rate that rises and then falls, while a short distance indicates a falling hazard rate.

The density function calculated by the Wiener process with absorption has the following specifications:

$$f(t \mid X) = \frac{c}{\sigma\sqrt{2\pi \cdot t^3}} \exp\left[-\frac{(c-\eta \cdot t)^2}{2\sigma^2 t}\right], \tag{2}$$

where $\eta = \exp(X'\beta)$, σ and β are the parameters that define the format of the conditional distribution and $c = \exp(Z'\gamma)$ is the component that determines the distance between the points of entry and absorption, based on the vector Z of characteristics and the vector γ of coefficients. It should be noted that when $c = \sqrt{\gamma^{-1}}$ and $\eta = \sqrt{\gamma^{-1}}/\lambda$, function (2) becomes identical to the inverse Gaussian distribution in (1).

We believe that the Wiener process controls in part the effect of re-entry into poverty, which is not taken into account due to the limitations of the panel data that we use. In other words, in accordance with their specific characteristics, certain households enter poverty already liable to remain in this situation for a longer period than others.

Iceland (1997a) argued that left-censoring is one of the main problems of poverty duration models. According to D'Addio and Rosholm (2002), duration models that control left-censoring are rarely found in the literature because they are difficult to estimate.[3] In addition, the general understanding is that left-censored observations do not contain relevant information that can be used empirically.

These authors also indicate that two solutions are usually adopted for the problem of left-censoring. Either a very limiting assumption of stationarity is made or all left-censored observations are omitted. However, in situations where there is a relatively short period of observation and the proportion of censored cases is high, the information contained in those cases is critical.

Therefore, we decided to make the assumption of stationarity to compensate for not limiting the sample in any way. Adopting this assumption implies assuming that the conditional rate or probability of entry into poverty is constant. On this basis, we calculated the duration models by maximising the likelihood function proposed by Amemiya (1999). When n_1 represents the number of left-censored cases and $n_2 = n - n_1$ is the number of the remainder of cases, Amemiya's probability function consists of an equation with two separate parts, according to the type of sample, which are multiplied by the respective probability of whether the information is left-censored or not:

$$L = \prod_{i=1}^{n_1}\left[\frac{S(t_i \mid X_i)}{E(T \mid X_i)}\frac{P_0(X_i)}{P_0(X_i)+P_1(X_i)}\right] \cdot \prod_{i=1}^{n_2}\left[\frac{e(\tau_i \mid X_i)h(t_i \mid X_i)S(t_i \mid X_i)}{P_1(X_i)}\frac{P_1(X_i)}{P_0(X_i)+P_1(X_i)}\right]. \tag{3}$$

In this function, t^i is the total time that the case I remains in the state and τ_i is the observed time of the case i in the state. $E(T \mid X_i)$ represents the expected duration of the case i and $e(\tau_i \mid X_i)$ is the rate of entry into the state at time τ_i. $P_0(X_i)$ and $P_1(X_i)$ are the probabilities of being in the state at time 0, before beginning the count, and at time 1, at the beginning of the count, respectively. X_i is the vector of the characteristics that determine the entry into and the permanence in the state under analysis.

If we assume a constant rate of entry into the condition, we can state that $e(\tau_i \mid X_i) = e(X_i)$, $P0(X_i) = e(X_i)E[T \mid X_i]$ and $P_1(X_i) = \tau_1 e(X_i)$. Therefore, function (3) can be simplified to:

$$L = \prod_{i=1}^{n} \left[\frac{h(t_i \mid X_i)^{d_i} S(t_i \mid X_i)}{E(T \mid X_i) + \tau_1} \right], \tag{4}$$

where $d_i = \{0,1\}$ is an indicator of whether the observation is left-censored or not and τ_1 denotes the observed duration from the first period onwards.[4]

V. Results

The Slope of the Probability (Hazard) Function for Exiting Poverty

Figure 2 shows that all the parametric hazard functions based on the full sample have a negative slope from the second month of the poverty spells onwards. Therefore, the longer a household remains in poverty, the greater are its chances of staying there. With the exception of the Weibull model, it is observed that, after the tenth month, the average probability of leaving poverty is less than 20 per cent.

The inverse Gaussian function indicates the most critical condition. According to this model, the mean probability of exiting poverty in the first month is less than

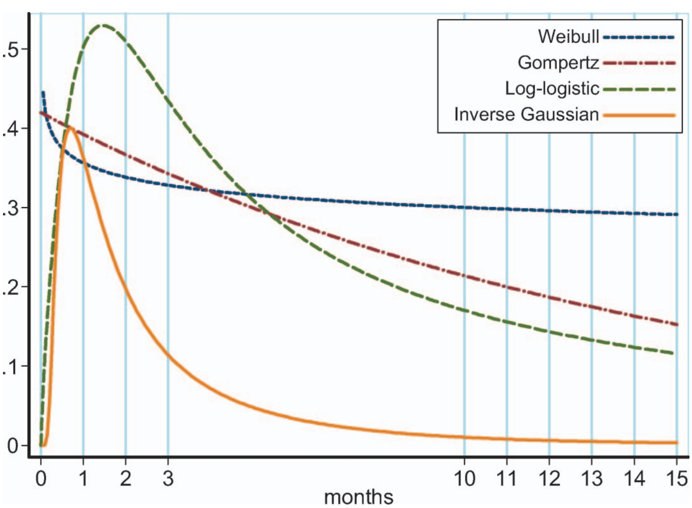

Figure 2. Parameterised probability (hazard) functions of exiting poverty. *Source*: Own elaboration based on the Monthly Employment Survey (PME) 2002–2007.

40 per cent. After the third month, the probability drops to less than 10 per cent and, after the tenth month, it is almost zero.

In order to verify whether the format of the hazard functions is heterogeneous according to the Wiener process, we tested the hypothesis that the parameter c in function (2) is constant. The chi-square statistics of the Hausman test (13362.29 with 25 df) indicate that the estimation of the Wiener process with absorption is more consistent than a simple estimation of an inverse Gaussian model. Thus there are households with a higher probability of leaving poverty immediately in the first month, just as there are households that, having fallen into poverty, are already subject to remaining in this situation for a long time. The estimated determinants of the distance between the starting and the absorption points are given in the Appendix (Table A1).

The Determinants of Leaving Poverty

Table 3 gives the results of the hazard function, estimated by assuming the Weibull, Gompertz, Log-logistic and inverse Gaussian (Wiener process with absorption) distributions. The regressions presented in this table estimate the effects of the household's fixed characteristics, obtained during the first month that it was observed in poverty.

In the regressions, almost all of the coefficients are significant. The exceptions are the coefficients related to the dummy variables for unmarried household head and unmarried female head. The effects of having mostly working-age members and having adults with a higher level of schooling are indirect indications of the positive role played by labour supply on the probability of exiting poverty.

The probability of exiting poverty is even greater the older the household head. Nonetheless, the presence of an elderly member in the household is more important than all other characteristics. This factor increases the chances of leaving poverty by more than 20 per cent. The reason for this might be the effect of retirement benefits on providing extra income for poor households. That is, the pensions paid to these elderly members probably contribute to reducing the depth of poverty (the poverty income gap), thus making it easier for these households to exit poverty when another member obtains additional income.

In general, many of these results were expected. For instance, the greater the distance of household per capita income below the poverty line, the lower the probability of moving out of poverty. However, this effect is significantly convex. Figure 3 presents the estimated hazard ratio according to the poverty income gap. These graphs show that the households that entered into poverty with zero income (namely, the gap is equal to one) are not the ones with the lowest probability of exiting from this condition. That is, the households that currently are most poverty-stricken are not the most chronically poor.

The households with a poverty income gap equal to one are probably the ones that temporarily lost their only source of income because, for example, the household head became unemployed. Nevertheless, such households have a greater chance of exiting poverty when the head or another working-age member of the household finds a new job than the households that have not undergone this change

Table 3. Regressions results for different duration models

	Weibull		Gompertz		Log-logistic		Inverse Gaussian	
	Hazard ratio	Coefficient	Hazard ratio	Coefficient	Odds ratio	Coefficient	Hazard ratio	Coefficient
MA Salvador	0.96763	−0.03290**	0.96360	−0.03708***	0.83375	−0.18182***	1.07912	0.07614***
MA Belo Horizonte	1.27206	0.24064***	1.24222	0.21690***	1.39104	0.33005***	1.33586	0.28958***
MA Rio de Janeiro	1.08136	0.07822***	1.07189	0.06942***	1.06876	0.06650***	1.14468	0.13513***
MA São Paulo	1.18567	0.17031***	1.16088	0.14918***	1.21272	0.19287***	1.26489	0.23499***
MA Porto Alegre	1.29204	0.25623***	1.25987	0.23101***	1.41824	0.34942***	1.33342	0.28774***
Log of the number of members	0.83593	−0.17921***	0.85443	−0.15732***	0.75071	−0.28673***	0.87353	−0.13521***
Extended household	1.05662	0.05507**	1.04486	0.04388**	1.11531	0.10914***	1.02957	0.02914
More than 50 per cent are working-age	1.15022	0.13995***	1.13267	0.12458***	1.32071	0.27817***	0.86382	−0.14639*
Presence of:								
one child or more	0.91890	−0.08458***	0.92279	−0.08035***	0.90982	−0.09451***	0.80215	−0.22045***
two children or more	0.84166	−0.17238***	0.85921	−0.15174***	0.69786	−0.35974***	0.86685	−0.14289***
one adolescent or more	0.90879	−0.09564***	0.91596	−0.08779***	0.88906	−0.11759***	0.79000	−0.23572***
two adolescents or more	0.96938	−0.03110*	0.96953	−0.03095**	0.98155	−0.01862	0.85019	−0.16230***
one elderly person or more	1.22268	0.20104***	1.20752	0.18857***	1.34476	0.29622***	1.26400	0.23428***
illiterate adult	0.96902	−0.03147*	0.97080	−0.02963*	0.97103	−0.02940	0.91253	−0.09153**
functionally illiterate adult	0.97031	−0.03014**	0.97348	−0.02688**	0.94976	−0.05155***	0.98057	−0.01962
adult with elementary education	1.05944	0.05774***	1.05208	0.05077***	1.12079	0.11403***	0.99574	−0.00427
at least two adults with elementary education	1.10257	0.09764***	1.08950	0.08572***	1.15790	0.14661***	1.11930	0.11271***
adult with high school	1.08563	0.08216***	1.07620	0.07344***	1.13326	0.12510***	1.09389	0.08974***
adult with college education	1.16096	0.14925***	1.15513	0.14422***	1.16266	0.15071***	1.30038	0.26266***
White head	1.02680	0.02645**	1.02633	0.02599**	1.05845	0.05680***	1.00624	0.00622
Unmarried head	0.98227	−0.01789	0.98243	−0.01773	0.99889	−0.00111	0.92823	−0.07448
Unmarried female head	0.99631	−0.00369	0.99535	−0.00466	0.99188	−0.00815	0.93741	−0.06463
Head's age	1.01094	0.01256***	1.01014	0.01152***	1.01828	0.03282***	1.01515	0.01706***
Head's age squared		−0.00002		−0.00002		−0.00016***		−0.00002
Poverty income gap	0.78376	−0.84113***	0.80403	−0.75411***	0.61997	−1.55680***	0.93260	−0.46405***
Poverty income gap squared		0.58418***		0.52406***		1.05472***		0.38550***
Constant		−1.29955***		−1.18945***		−1.70628***		−1.08123***
Parameter of the hazard function	p	0.92549***	gamma	−0.06742***	gamma	0.56365***	c[1]	1.45594***

Note: [1]This value represents the mean of the sample since it was parameterised according to some of the covariates. The coefficients of the regression of the logarithm of c can be found in the Appendix. *significant at 5 per cent level; **significant at 1 per cent level; ***significant at 0.1 per cent level; and MA = Metropolitan Area.
Source: Own calculations based on the Monthly Employment Survey (PME) 2002–2007.

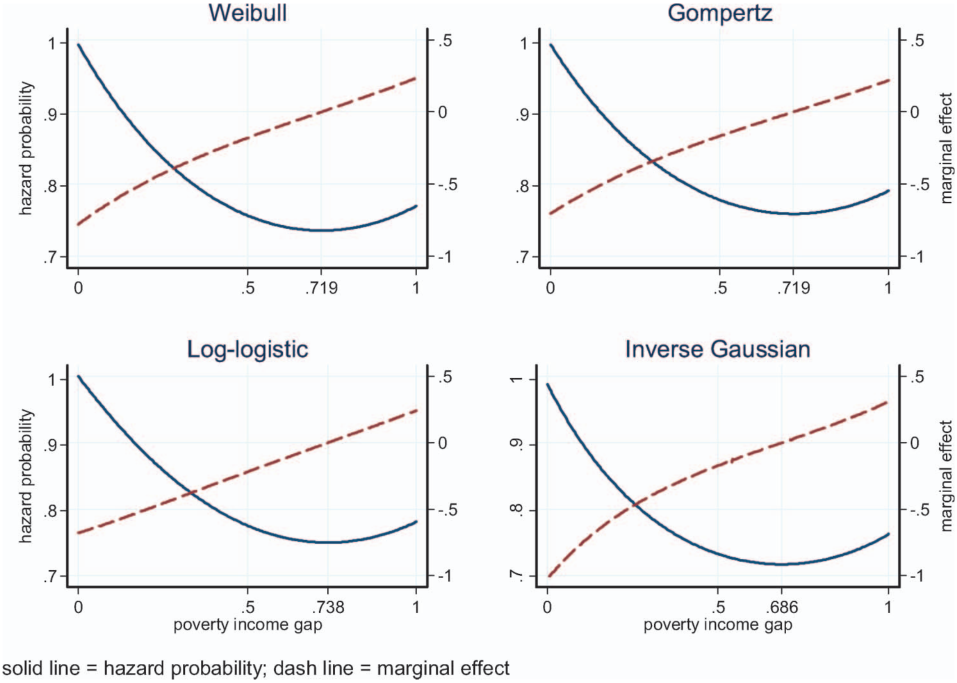

Figure 3. Effect of the initial poverty income gap on the probability of exiting poverty. *Source*: Own elaboration based on the Monthly Employment Survey (PME) 2002–2007.

but continue to receive a low level of income that is insufficient to sustain their members.

The Effect of Labour Market Changes on Exiting Poverty

According to Cardoso (2007), the period between 1999 and 2003 is characterised by restrictive fiscal and monetary policies, with significant surplus in the commercial balance. Such scenario resulted in a stable unemployment rate, declining informality, and decreasing real wages. After 2003, the growth of the commodity market, the increase of the minimum wage, the expansion of cash transfer programmes and public credit, and the slight decrease of the interest rate led to a growth of the aggregate demand. These changes were followed by reduction in the unemployment and informality rates and a small increase in wages among low-income workers, which contributed significantly to reduce income inequality.

Considering this context, inspired by the study of Iceland (1997b), we constructed time-varying covariates that represent changes in the labour market in order to estimate the effects of aggregate demand on poverty duration. Specifically, we analysed the effects of quarterly variations in: (1) the proportions of employees in the sectors of industry, commerce and construction in relation to the service sector; (2) in the unemployment rate; and (3) in the average real wage of civil servants, the self-employed, and registered and unregistered employees.

Table 4 describes the magnitude of these variations during a period of 60 months (from June 2002 to May 2007) in the six previously mentioned metropolitan areas. It shows that, in spite of the averages being close to zero, the deviations are large enough to make it possible to analyse the impact of these changes.

In order to include these covariates, which change over time, in the estimation of the duration model, we had to expand (split) the sample, including for each household all the months in which it was interviewed and was in poverty. The consequence of this expansion on the sample has already been shown in Table 2. The results of the estimated probability of exiting poverty for this new sample are shown in Table 5.

All of the models use the households' fixed covariates and include time-varying covariates in stages. The first model considers only the fluctuations in all employees' average wage. The second model specifies the variation in average income according to occupation. The third model includes the variation in the unemployment rate. And the fourth model includes the variations in the proportion of employees by sector. The last, and most complete, model incorporates dummy variables for months to control for seasonality.

According to the coefficients that were estimated, we found that a quarterly increase of one per cent in average earnings actually reduces the probability of exiting poverty by between 0.6 and 0.9 per cent. A possible explanation for this result is that the rise in the average wage causes an increase in the labour supply of more skilled workers and that this, in turn, creates greater difficulties for the insertion of less skilled workers in the formal labour market. In other words, the consequence of the rising average wage might be the rise in the unemployment rate for workers with low qualifications.

Decomposing this effect by the type of occupation, we find that a quarterly increase of one per cent in the average income of registered workers actually reduces the probability of exiting poverty by 5 to 9 per cent. But the same growth in the earnings of unregistered workers increases this probability by 6 to 12 per cent.

Table 4. Descriptive statistics of aggregate changes

Variation (%) in	Mean	Standard deviation	Minimum	Maximum
average wage of all employees	−0.1146	3.5527	−16.5691	12.1042
average wage of self-employed workers	−0.3332	7.3220	−32.4074	22.8641
average wage of registered employees	−0.0255	3.6118	−12.8106	13.3582
average wage of unregistered employees	1.2207	3.3574	−11.2621	15.2554
average wage of civil servants	0.2407	5.7320	−18.4483	20.2215
unemployment rate	−0.2946	10.0339	−26.1539	39.5833
proportion of employees in industry	−0.0479	4.3228	−17.1920	18.2049
proportion of employees in construction	0.1114	6.5141	−17.8042	25.7944
proportion of employees in commerce	−0.2843	3.8151	−14.5585	10.4305
Number of Metropolitan Areas	6			
Number of months	60			
Total observations	360			

Source: Monthly Employment Survey (PME) 2002–2007.

Table 5. Effects of aggregate changes estimated using different models of poverty

	(1)	(2)	(3)	(4)	(5)
Effect of quarterly variation on:			Weibull model – hazard ratio		
average wage of all employees	0.9925***				
average wage of self-employed workers		0.9984***	0.9983***	0.9989**	0.9976***
average wage of documented employees		1.0707***	1.0726***	1.0777***	1.0988***
average wage of undocumented employees		0.9386***	0.9379***	0.9329***	0.9183***
average wage of civil servants		0.9983***	0.9982***	0.9990*	0.9982***
unemployment rate			0.9973***	0.9972***	1.0001
proportion of employees in industry				0.9945***	0.9932***
proportion of employees in construction				0.9995	1.0004
proportion of employees in commerce				0.9888***	0.9908***
Effect of quarterly variation on:			Gompertz model – hazard ratio		
average wage of all employees	0.9939***				
average wage of self-employed workers		0.9986***	0.9986***	0.9991*	0.9980***
average wage of documented employees		1.0585***	1.0600***	1.0645***	1.0822***
average wage of undocumented employees		0.9490***	0.9485***	0.9440***	0.9314***
average wage of civil servants		0.9984***	0.9984***	0.9990*	0.9984***
unemployment rate			0.9976***	0.9975***	1.0001
proportion of employees in industry				0.9953***	0.9941***
proportion of employees in construction				0.9994	1.0002
proportion of employees in commerce				0.9901***	0.9919***

(*continued*)

Table 5. (*Continued*)

	(1)	(2)	(3)	(4)	(5)
Effect of quarterly variation on:			Log-logistic model – odds ratio		
average wage of all employees	0.9937***				
average wage of self-employed workers		0.9980***	0.9980***	0.9988*	0.9976***
average wage of documented employees		1.0619***	1.0632***	1.0688***	1.0887***
average wage of undocumented employees		0.9481***	0.9478***	0.9421***	0.9280***
average wage of civil servants		0.9972***	0.9971***	0.9980**	0.9970***
unemployment rate			0.9973***	0.9971***	1.0008
proportion of employees in industry				0.9949***	0.9936***
proportion of employees in construction				0.9983**	0.9993
proportion of employees in commerce				0.9871***	0.9895***
Effect of quarterly variation on:			Inverse Gaussian model – hazard ratio		
average wage of all employees	0.9911***				
average wage of self-employed workers		0.9989	0.9988*	0.9998	0.9976***
average wage of documented employees		1.0831***	1.0862***	1.0934***	1.1187***
average wage of undocumented employees		0.9291***	0.9279***	0.9212***	0.9049***
average wage of civil servants		0.9973***	0.9973***	0.9982*	0.9971***
unemployment rate			0.9966***	0.9965***	0.9999
proportion of employees in industry				0.9927***	0.9913***
proportion of employees in construction				0.9996	1.0014*
proportion of employees in commerce				0.9852***	0.9874***
Control variables					
Household fixed characteristics	X	X	X	X	X
Dummy for months of the year					X

Note: *significant at 5 per cent, **significant at 1 per cent, ***significant at 0.1 per cent.
Source: Own calculations based on the Monthly Employment Survey (PME) 2002–2007.

According to Machado et al. (2007), poor workers are concentrated in the informal sector in Brazilian metropolitan areas. Thus, one can assume that the effect on unregistered workers tends to increase the income in poor households, whereas the effect on registered workers leads to a lower participation of poor workers in the formal labour market.

Table 4 shows that, fortunately for poor households, earnings in the informal sector have been increasing more quickly, on average, than in the formal sector. Part of this growth can be attributed to the re-adjustments in the minimum wage. As Giambiagi and Franco (2007) and Camargo et al. (2001) note, the so-called 'light-house' effect of the minimum wage has a substantial impact on the informal labour market. The employer who does not officially register workers is not forced to readjust his wages because he is already acting illegally. However, moral considerations (the need to obey social norms) and/or the practical necessity to avoid worker dissatisfaction can lead the employer to follow the law regarding the minimum wage, even if this is done in an informal manner.

Supporting this evidence, Khamis (2008) claims that increases in the minimum wage usually have more impact on the informal sector than on the formal sector in developing countries. He shows that two minimum wage readjustments, in 1993 and 2004, significantly raised wages in the informal sector in Argentina, whereas they had no impact in the formal sector's wages. In addition, Gindling and Terrell (2004) find that the minimum wage raises earnings not only in the urban formal sector but also in informal sectors in Costa Rica.

These results present the role of the minimum wage over the informal workers earning and, consequently, over the proportion of poor. When there is no control for seasonality, we found that the direct effect of reducing the unemployment rate by 1 per cent on the probability of exiting poverty is only 0.3 per cent. When seasonality is controlled, this effect is no longer significant. Therefore, exogenous shocks in unemployment, which are not related to the variation of other observable variables, do not affect a household's permanence in poverty. Namely, changes in the unemployment rate may affect poverty duration only when these are promoted by variations in wages or predicted by seasonal fluctuations of economic activity.

It is worth mentioning that formal employees are the only ones covered by unemployment insurance in Brazil and, as already pointed, they are under-represented in poverty. According to Tzannatos and Roddis (1998), this system is different in other countries, like Canada and Denmark, where self-employed wokers are covered too. Therefore, when formal workers lose their jobs, they rarely fall into poverty. On the other hand, when informal employees become unemployed in Brazil, they depend only on odd jobs to sustain themselves. Finally, variations in the aggregate unemployment rate may not affect a great part of the informal sector, which corresponds to the self-employed, since this part is only related to labour supply decisions.

With regard to the participation of employees by sector, we can see that the reduction of 1 per cent in the proportion of industrial and commercial workers in relation to service-sector workers increases the probability that households will leave poverty by around 0.5 to one per cent, respectively. That is to say, the movement of industrial and commercial workers into the service sector in metropolitan areas significantly reduces the period spent by households in poverty. However, according to Table 4, on average, this change has been taking place very slowly. Between 2002 and 2003, such variation took place mainly in the personal sevice sector. After 2003, the productive service sector, which correspond to financial services, communication, and company services supply, and the social service sector, which includes health and education, grew faster than the others (Cardoso, 2007).

As a final note, the effect of changes in the proportion of employees in the construction sector is not significant in most of the models analysed.

VI. Conclusion

The results of the parametric survival models suggest that the probability of moving out of poverty decreases the longer the household has remained in poverty – mainly after the second month in this condition. Therefore, the longer the household stays in poverty, the greater the chances that it will remain there.

With regard to households that have entered poverty, we found that, in general, the greater the distance of their initial per capita income below the poverty line, the lower the probability of their exit from poverty. However, the households that entered into poverty with no income, or very low incomes, are not the ones with the lowest chance of exiting this state. For some households, the transitory nature of unemployment of the household head or other key working members puts them in the situation where their poverty income gap might be large but the probability of remaining in poverty is actually lower than that for households that have somewhat higher incomes but their poverty-level income is long-lasting.

In terms of changes in the labour market, we found that the movement of industrial and commercial workers into the service sector in metropolitan areas has caused a significant reduction in the length of time that households spend in poverty. However, this movement has, on average, been taking place very slowly. In fact, this process of 'tertiarization' might be already beginning to wane. Another important result is that changes in the unemployment rate do not have a *direct* effect on the likelihood of households remaining in or exiting poverty.

In the regression analysis, we also showed that increasing the average wage of the workers who were registered caused a significant reduction in the probability of the exit of poor households from poverty, whereas the increase of the average earnings of unregistered workers raised this probability to a significant degree. Indeed, poor workers are more concentrated in the informal than in the formal sector of the economy. Therefore, the increase in the average earnings of informal workers has the effect of increasing the income of poor households, while an increase in the wage of the rest of the formal-sector workers does not have the same effect.

We should take into account that, in Brazil, there is an enormous contingent of adults who face a huge difficulty in participating in the labour force, especially in the formal sector of the economy. For this group, job creation programmes could be ineffective in helping them exit poverty. In addition, increases in the average wage among formal-sector workers might make the participation of poor workers in the formal labour market even more difficult. Thus, the common strategy adopted by such workers in order to mitigate their conditions is to take up employment in informal low-paid jobs.

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Notes

1. The poverty lines were deflated in accordance with the modified INPC proposed by Corseuil and Foguel (2002), which can be found at http://www.ipea.gov.br/sites/000/2/publicacoes/tds/td_0897.pdf
2. The generalised Gamma distribution, which represents the general case of exponential, Weibull and Log-logistic distributions, was not taken into account because the maximum likelihood estimation of this model did not converge.
3. See Gritz (1993) and Rosholm (2001) as references.
4. D'Addio and Rosholm (2002) propose another likelihood function that produces more robust results. However, using this function requires retrospective data about events prior to the situation under analysis.

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Appendix

Table A1. Regression coefficients of the logarithm of *c* according to the Wiener process (inverse Gaussian distribution)

	Coefficient
MA Salvador	0.08115***
MA Belo Horizonte	0.01441
MA Rio de Janeiro	0.02267*
MA São Paulo	0.03430***
MA Porto Alegre	0.01037
Log of number of members	0.03053*
Extended household	−0.02513
More than 50 per cent are working age	−0.17938***
White household head	−0.01299
Unmarried household head	−0.03061
Unmarried female head	−0.01806
Head's age	−0.00801***
Head's age squared	0.00009***
Constant	0.60491***
Presence of:	
one child or more	−0.06239***
two children or more	0.06510***
one adolescent or more	−0.05283***
two adolescents or more	−0.06011***
one elderly person or more	0.00428
illiterate adult	−0.04119***
functionally illiterate adult	0.00598
adult with elementary school	−0.03335***
two adults with elementary school	−0.00366
adult with high school	−0.00445
adult with college education	0.08517***
Poverty income gap	0.26961***
Poverty income gap squared	−0.15860***

Note: *significant at 5 per cent; **significant at 1 per cent; ***significant at 0.1 per cent; MA = Metropolitan Area.

Source: Own calculations based on the Monthly Employment Survey (PME) 2002–2007.