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SOCIAL INEQUALITY IN THE ACCESS TO HEALTHCARE SERVICES IN BRAZIL

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SOCIAL INEQUALITY IN THE ACCESS TO HEALTHCARE SERVICES IN BRAZIL

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1. INTRODUCTION

The major health policy goal in most countries has been the promotion of an equitable healthcare distribution. However, empirical works point out to a general healthcare inequality which favors more privileged social groups. Brazilian studies also indicate social health inequality favoring high-income groups[1]. This result can be a consequence of differences in the amount of medical assistance between socioeconomic groups. Empirical evidence shows that there is inequality in the access to healthcare in some countries which is favorable to the wealthy[2]. Such an outcome was even observed in developed countries where economic disparities are not so outstanding and in countries in which healthcare services are free of charge.

The social inequality in health and the way healthcare services supply is organized in Brazil suggest the presence of social inequality in the access to such care. The Brazilian healthcare market is characterized as a mixed system both in funding and provision, implying two different types of access. Firstly, a common public healthcare system is offered – the *Sistema Único de Saúde* (SUS). In this case the supply of health care services is universal, comprehensive, and free. Secondly, there are the health care services funded and provided by the private sector. In this case the access is guaranteed against out-of pocket payment to providers or by adhesion to a health insurance plan.

This aim of this paper is to test the hypothesis of horizontal equity in the access to healthcare services in Brazil, considering outpatient and inpatient care separately. This paper intends to verify whether individuals having equal needs are granted the same healthcare level, independently of their socioeconomic characteristics. The estimation method is based on the *hurdle negative binomial* model (*hurdle negbin*) which estimates the use of healthcare services in two stages. The database used is PNAD/98 – Pesquisa Nacional de Amostra Domiciliar (the Brazilian National Household Sample Survey), which presents a special survey on health issues. For every type of health care we considered two different samples: the first one including all age groups and the second one including only the occupied population at active age (individual between 15 and 65 years old). The latter exercise is crucial as it allows that the individuals' occupational characteristics be taken into account.

The major contribution of this paper is to estimate social inequality in the access to the Brazilian healthcare services by using the hurdle model. The findings show that inequality in the access to healthcare services is differentiated, according to the kind of healthcare focused. When considering ambulatory services, we found in the two samples that the greater the family per capita income, the greater the probability of an individual to visit a doctor. This is also observed even when the morbidity and occupational characteristics and the existence of a healthcare plan are controlled. The expected number of medical visits is responsive to income only when the sample is restricted to occupied individuals. The greater the income, the greater the number of doctor visits. A possible explanation for such an outcome is that, when the total population is considered, the most vulnerable population groups in terms of health status - children and the elderly, who can not postpone medical assistance – are included.

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[1] For international literature, see Pereira, 1995 e Doorslaer et al, 1997. For the Brazilian case, see Noronha e Andrade, 2001, Campino et al, 1999, and Travassos et al, 2000.

[2] Pereira, 1995, Doorslaer e Wagstaff, 1992 e Waters, 2000.

Related to inpatient care we observed that the probability of individuals to be hospitalized and the time span are greater for the poorer, if the whole sample is considered, characterizing inequality in the access in favor of the poor. Such a result, however, should be interpreted with caution, as health measures used may not be capturing the differences in the degree of morbidity between the poor and the wealthy. Poorer individuals may present a more precarious health status when they look for healthcare, needing a more intensive treatment.

This paper is divided into five sections beyond this one. In the next section, both a review concerning the usually employed methods in the international literature and the empirical evidence in Brazil will be made. The third section presents a brief description of the database and variables used. The fourth section discusses the methodology. The major outcomes are presented in the fifth section. The last section presents the final remarks.

2. REVIEW OF THE LITERATURE

2.1. Review of the International Empirical Literature

Social inequality in the access to healthcare services has been widely analyzed in several empirical works in the international economic literature. The criterion usually adopted is based on horizontal equity principle (individuals with equal healthcare needs should be treated in the same way). Based on such principle, health care services should be distributed in accordance with the healthcare needs of each individual, independently of his/her socioeconomic characteristics. Basically, there are two ways of verifying if the healthcare system follows the equity principle.

The first consists in measuring inequality in the access of healthcare services. Initially, empirical works reported in the international literature were based on the construction of concentration curves relating the access to healthcare services to morbidity incidence in each socioeconomic group. Le Grand (1978) pioneered the use of such a methodology which was further developed by Doorslaer and Wagstaff (1992). Based on such a methodology, Campino et al (1999) measured the social inequality in the access to healthcare services in Brazil. The authors measured the access to health care services through utilization which allowed them to build two concentration curves: the first unstandardized and the second standardized by age, sex, and morbidity. The results encountered suggest the existence of social inequality in the preventive and curative health care services favoring higher income groups.

A second way of evaluating inequality in the access to healthcare services consists in estimating a regression model whose dependent variable encompasses a utilization measure. The first work to employ such a method was developed by Cameron et al (1988). The authors estimated an equation of health services utilization for Australia, based on a binomial negative model to verify the frequency in which individuals used healthcare services. The major contribution of this paper was to consider the health insurance choice as an endogenous variable.

Some authors have proposed to estimate the model of healthcare services utilization in two stages. In the first stage, the probability of people receiving or not healthcare services would be estimated; and in the second stage, the amount of health care services would be estimated considering only individuals in the sample with positive utilization. In the first estimation stage, a binary probability model (Logit or Probit) is used for estimating whether the individual searched or not for any healthcare service. The estimation in the second stage may be accomplished in several ways. One of these consists in estimating the regression for a frequency decision by the Ordinary Least Square method (OLS)[3]. The weak point of such a method is that data on utilization of healthcare services are censored. When estimating by OLS, this particularity of the sample is ignored[4]. A second way consists in estimating a *hurdle* model in which the second stage is estimated adopting a truncated at zero negative binomial model[5]. Gerdtham (1997) and Pohlmeier and Ulrich (1994) use this methodology for testing the horizontal equity in the access to healthcare services in Sweden and Germany, respectively considering the adult population. In the two studies, contact decision and the frequency decision are determined by distinct stochastic procedures which suggest that estimation through the hurdle model is more adequate.

Both works estimate separate models for the different health care specialties. Gerdtham (1997) distinguishes the ambulatory services from inpatient care. According to the author, such demands can not be interpreted in the same way, due to the fact that the probability of hospitalization depends mainly on a physician's decision, whereas the probability of a doctor visit depends on the decision of the individual him/herself. Pohlmeier and Ulrich (1994) distinguish the generalist doctor from the specialist doctor. Such a distinction is relevant, due to the characteristics of healthcare services in Germany. Access to specialist physicians is mainly accomplished through an referral from a generalist physician which thus defines differentiated behaviors in relation to healthcare services demand between the two medical specialties.

2.2. A Review of the Brazilian Empirical Literature

As far as the Brazilian case is concerned, there are some papers which attempt to measure social inequality in the access to healthcare services. Almeida et al (2000), based on the PNSN[6] for the year of 1989, estimated a healthcare service utilization rate for each income quintile. These rates were standardized by sex and age and obtained separately for sick and healthy individuals. The healthcare service utilization is strongly unequal among the socioeconomic strata, favoring the higher-income levels. Approximately 45% of the individuals belonging to the first quintile with activities restrained due to illness use healthcare services. This percentage increases to 69.22% when higher-income groups are considered. For the sample of healthy individuals, the fifth quintile shows a utilization rate 50% higher than that for the lowest-income stratum.

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[3] Alberts et al, 1997, and Doorslaer and Wagstaff, 1992.

[4] Some authors also point out to the problem of sample selection bias. In this case, the model used is based on the methodology developed by Heckman (1979), consisting in estimating, in the first stage, an equation for the search of health services through the Probit model through which a correction factor of the sample selection bias is obtained. Such a factor is included in the regression model to estimate, through the LOS, the frequency of doctor visits. See, e.g., Newbold, Eyles and Birch (1995).

[5] The hurdle model was initially proposed by Mulahy (1986), and is used by some authors in the analysis of the access to health services.

[6] A national survey on health and nutrition.

Travassos et al (2000) estimated odd ratios for three income groups by using a PPV for the years of 1996/1997[7]. The authors showed that there is social inequality in the distribution of healthcare in the country, which is favorable to privileged social classes. The chances of an individual of the first tercile to use healthcare services is 37% smaller in the Brazilian Northeast and 35% smaller in the Southeast, as compared to individuals in the third tercile. Utilization chances are also greater among individuals covered by health insurance plans *vis à vis* those not covered (66% greater in the Northeast and 73% in the Southeast).

Viacava et al (2001), based on data from the PNAD/98 (the National Household Sample Survey), tested the existence of social inequality in health services utilization by gender. They also estimated odds ratios. The authors observed that individuals with higher education degree, employers, formal sector employees, and whites have greater chances to search for healthcare services both preventive and curative services. This indicates social inequality in the consumption of such services, favoring more privileged social groups.

Empirical studies in Brazil suggest the presence of social inequality in the access to healthcare services. The aim of this paper is to go further in this discussion using a methodology that allows us to evaluate if the existing inequality in this market is related to the contact decision or to the frequency decision - the amount of treatment to be received by the patient.

3. DATABASE AND DESCRIPTION OF VARIABLES

The database used was the PNAD/98, accomplished by the *Instituto Brasileiro de Geografia e Estatística* – IBGE – (the Brazilian census bureau), containing information on individual characteristics, such as education level, individual and family income, age, among others. In 1998, the supplement of PNAD focused on health issues[8]. 344,975 people were surveyed all through the national territory, except for the Northern region's rural area. For this reason, all the federative units of this region were excluded from the analysis which reduced the number of observations to 318,909[9].

The dependent variables encompass a measure of physician care and hospitalizations[10]. These variables were obtained from questions in PNAD/98 which allowed us to know whether the individuals had visited the doctor and on what frequency as well as whether they had been hospitalized and for how long in the 12 months previous to the survey[11].

The independent variables may be classified into three groups. The first comprises socioeconomic and demographic variables. A set of dummies for per capita family income, head of

[7] A survey on standard of living.

[8] The information contained in the supplement were mostly given by only one person living in the household. 36.08% out of the respondents in this part corresponded to the person him/herself.

[9] The sample size varied in accordance with the estimated model due to those missing in the dependent and independent variables used in each model.

[10] There are several ways to measure the access to healthcare services. A measure of healthcare services utilization is usually used. Another method, i.e., through expenditure, is generally used.

[11] Concerning medical appointments, the PNAD/98 also includes another question using a period of 2 weeks as reference. This question was not used, because the demand for services was declared by a very small percentage of individuals and this made it impossible a more detailed analysis.

family education, race, gender, and family composition is considered. Furthermore, we included a discrete variable referring to the number of family members as well as two variables related to age - a linear and a quadratic term. In the model estimated for the occupied population at working age, variables related to individual occupation characteristics, such as occupied position, number of workhours, and branches of activity, could be taken into account.

The individuals were grouped according to their income decil[12]. To account for education, the sample was classified into nine groups according to the schooling of household head[13]. This variable is more appropriate than that of the own individual's education as it allows to include people at school age in the sample. Differences in healthcare services utilization may also occur among ethnic groups, due mainly to their relation to the individuals' socioeconomic position. PNAD/98 included whites, blacks, Asians, mestizos, and Indians in the sample. Only two categories will be considered in this paper, however: whites and nonwhites.

The family size effect is ambiguous. On the one hand, family size may positively affect the decision to use healthcare services due to the existence of economies of scale as healthcare cost is nonlinear in the number of family members. For example, when she takes a child to see the doctor, a mother may decide to take the other children too, as the opportunity cost of taking the other children is null for her. On the other hand, it is possible for the parents of a larger family to acquire some knowledge relating healthcare as they have more children (learning by doing) and thus becoming less dependent on healthcare services when a child becomes ill. In this case, the effect of this variable is negative. Furthermore, the composition of family expenses may vary according to its size thus changing the participation of health expenses in the total family budget.

The effect of family size largely depends on its composition, as health expenses and usage of such services are closely related to the age of their members. In this paper, the variable family composition was constructed by IBGE. PNAD/98 ranks the individuals into ten groups according to the kind of family which they belong to[14]. Due to the small number of observations, individuals belonging to families comprised by the couple or the mother, whose children's age had not been declared, were aggregated in the group referring to "other kind of family".

The proportion of individuals using medical services and hospitalizations and the frequency with which they are used is very differentiated among age groups. These services are expected to be more used by the extreme age groups, meaning that the children and the elderly need more such care than the other age groups. A continual age variable containing a linear term and a quadratic term and a binary variable for men were used in order to control such an effect.

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[12] Individuals whose family income is equal to zero were included in the sample. Such individuals represented 3% of the total sample (9,099 observations).

[13] Illiterate and those with less than one year of education, incomplete elementary school, complete elementary school, incomplete junior high school, complete junior high school, incomplete senior high school, complete senior high school, incomplete higher learning, complete higher learning.

[14] Couple with no children, couple with all their children below 14, couple with all their children over 14, couple with their children below 14 and over this age, couple with children of undeclared age, mother with all her children below 14, mother with all her children over 14, mother with children over and below 14, mother with children of undeclared age and other kind of family.

The dummy variables related to the occupational characteristics were included in the estimated model for the occupied population at working age[15]. Such variables allow to measure the opportunity cost for searching for any healthcare service. The time devoted to work implies less available time to see a doctor. Furthermore, depending on the way individuals enter the labor market, their opportunity cost is greater. People working in the informal labor market are generally paid per worked hour and are not protected by labor legislation. Thus, leaving work activities may result in income loss. The greater the loss, the greater the opportunity cost in demanding medical assistance. Two worked-hour groups were considered: those working between 1 to 39 hours per week and those working 40 hours or more.

In PNAD/98, the individuals were ranked into 12 positions in the occupation. Based on these categories, we constructed seven groups: registered employees in the formal sector; the military and public servants; unregistered employees (informal sector employees); house servants, independently of being registered or not; self-employed workers; employers; own-consumption production workers; own-use construction (building) workers; and unpaid family workers. Concerning the branches of activity, PNAD/98 specifies eleven categories[16]. This variable allows the particularities of the labor to be considered. Some activity branches are associated to a greater health hazard, implying a greater demand for medical and hospital assistance.

The second group of variables refers to supply characteristics. Different levels of access to healthcare services may be related to differences in the supply of such services among the localities. As such information is not provided by PNAD/98, dummies were included for the federative units and for localization of residences (urban/rural), considering that the supply of healthcare services vary greatly among the states and is precarious in rural areas.

In the model estimated for the ambulatory services, a dummy variable was included for the existence of health insurance coverage in the two estimation stages. The healthcare plan establishes a better condition of access and the utilization of such services is greater. In the case of hospitalization, this variable was included only in the first stage of the model. In the second stage, it was possible to verify whether the individual was hospitalized through the SUS or not. A difficulty in such variable was that 3.48% of the hospitalized individuals were not able to inform whether the service was covered by this system. As the services provided by the SUS should be free of charge, the individuals who did not pay any value for hospitalization were considered to be included in the SUS. In the same way, if the individuals paid any value for such hospitalization, they were considered as not included in the SUS system[17].

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[15] All variables related to occupational characteristics refer to the individual's situation in the previous two weeks of reference.

[16] Agricultural activities, manufacturing, civil construction, other industrial activities, merchandize trading, service rendering, aid services in economic activities, transport and social communications, public administration, and other activities.

[17] We concluded that 94.22% of the individuals who were not able to inform whether they were included in the SUS system did not pay any value for the hospitalization. The criterion adopted in this paper to classify such individuals as covered or not by the SUS does not entirely solve the problem, since the individuals who paid any value for the hospitalization (23.19%) were covered by the SUS.

The third group refers to the variables of the individuals' needs. Four indicators related to the individuals' health status were used. The first refers to some possible problem of physical mobility[18]. Individuals over 14 years of age were asked whether they had any difficulty in accomplishing their daily tasks[19]. The question allows four answer categories: "unable", "have great difficulty", "have little difficulty", "have no difficulty". The second indicator used was the number of chronic diseases. PNAD/98 formulated questions on the existence of 12 kinds of chronic diseases[20]. The figures of such a variable ranged from 0 to 11, indicating the total number of chronic diseases declared by the individual.. The third variable refers to a measure of self-assessed health status. PNAD/98 takes into account five different answer categories: very good, good, fair, poor, or very poor. The fourth indicator of need is a dichotomic variable informing whether the individual had suffered any difficulty in his/her customary activities, due to any health problem in the weeks previous to the survey. All health variables, except for the number of chronic diseases, were modeled in order to include dummy variables.

As far as hospitalization is concerned, it was possible to include – in the second stage of the model - a variable indicating the major healthcare service received when the patient was hospitalized. The following categories were specified: general clinical treatment, delivery, cesarean, surgery, psychiatric treatment, and medical examinations. Such a variable is relevant as the number of days in the hospital may vary, in accordance with the different kinds of treatment received, and due to the fact that it is associated with distinct morbidity patterns.

3.1. Descriptive Analysis of the Behavior of Major Variables

56% of the interviewed people had been given some kind of healthcare in the previous 12 months and the average number of medical visits was equal to 3.9. The proportion of hospitalized individuals was equal to 6.9% and the average number of days in the hospital was equal to 6.43 (Table 1).

TABLE 1. Usage of Healthcare Services: Brazil

Individuals who had demanded healthcare services (%)	Average number of medical visits per individual	Hospitalized individuals (%)	Average number of days in the hospital per individual
56	3.88 (4.87)*	6.93	6.43 (13.88)*

Source: PNAD 98.
* Standard deviation

[18] Questions about physical mobility were only answered by individuals over 14 years of age. 49.75% of the people responding to this part of the survey corresponded to those with own-experience responses.

[19] PNAD/98 asked the individuals whether they usually had any difficulty in feeding, bathing by themselves, using the toilet; running, lifting heavy things, practicing sports, or accomplishing heavy work tasks; moving a table or accomplishing domestic repairs, among others.

[20] Spinal column disease, arthritis or rheumatism, cancer, diabetes, bronchitis or asthma, hypertension, heart disease, chronic renal disease, depression, tuberculosis, tendinitis, and cirrhosis.

The percentage of individuals who had had an appointment with a physician increased monotonically with the per capita family income (Table 2).

TABLE 2. Usage of Healthcare Services by Income Deciles[1]

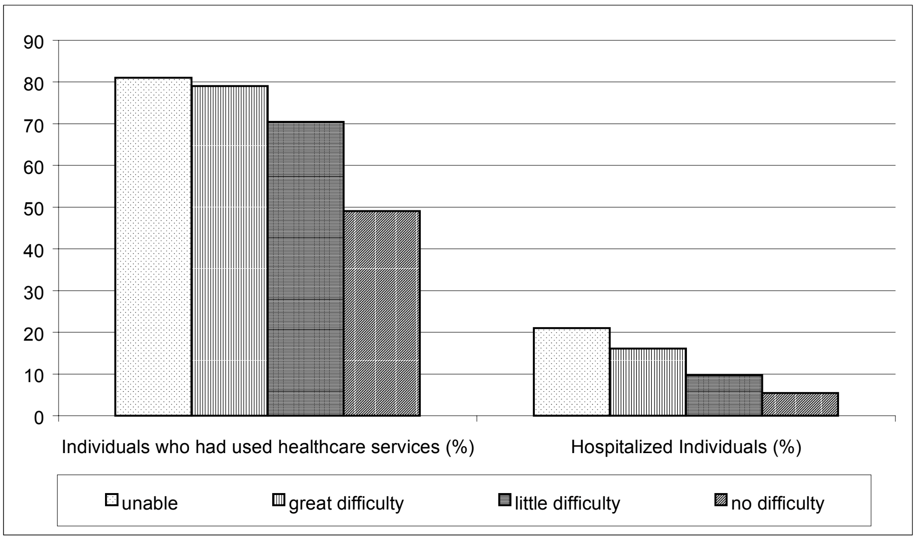
Income Deciles	Individuals who had used healthcare services (%)	Average number of visits	Hospitalized Individuals (%)	Average Number of Days in the Hospital
1	46.76	3.47 (4,3)	8.14	5.78 (12.14)
2	48.24	3.5 (4.39)	7.38	6.18 (11.76)
3	51.11	3.63 (4.51)	7.18	7.08 (15.58)
4	52.67	3.68 (4.72)	6.95	6.3 (12.92)
5	53.44	3.79 (4.84)	6.43	6.7 (14.98)
6	57.51	4.12 (5.3)	7.63	7.51 (16.87)
7	57.52	3.9 (4.61)	6.34	6.77 (14.6)
8	59.87	4.11 (5.36)	6.40	6.49 (12.78)
9	63.42	4.13 (5.09)	6.23	6.17 (14.6)
10	70.62	4.21 (5.11)	6.61	5.40 (11.82)

Source: PNAD 98.
1. The values in parentheses correspond to the standard deviation.

In spite of the fact that the average number of medical visits was larger for the last decile, the variation among groups was not very significant. As for hospitalization, the opposite occurred. The percentage of hospitalized individuals was larger among the groups with lower income. On the other hand, the average number of days in the hospital did not vary among the social strata (Table 2). These results seem to suggest that low-income people look for the doctor when their health conditions are worsened and they need a more intensive treatment. The results found for the education variable confirm those found for income. The greater the family head's education, the greater the proportion of individuals using ambulatory services and the greater the average number of medical appointments. The proportion of hospitalized individuals was larger among those whose family head's education was smaller and the average number of days in the hospital did not vary much among the groups.

The use of healthcare services was larger among individuals with worse health conditions, independently of the morbidity indicator used. In Graphic 1, it can be observed that the proportion of individuals who had used healthcare services was larger among those who were not able to accomplish or had had great difficulty in accomplishing some daily tasks.

GRAPHIC 1: Proportion of individuals who had used healthcare and hospital services, considering any difficulty degree in accomplishing tasks



Source: PNAD 98

As for the variable of self-assessed health status, approximately 80% of those who evaluated their health status as being poor or very poor had used ambulatory health services. Such a percentage was around 45% among those evaluating their health status as being very good. The percentage of individuals who had used healthcare services was larger among those declaring to present any hindrance to their activities in the reference period. Almost 90% of individuals with some restriction have had a medical appointment as opposed to 50% of those who did not present any hindrance. As to hospitalization, such a percentage was equal to 20% and 5%, respectively. The proportion of individuals who had used healthcare and hospital services as well as the average number of visits to the doctor and the number of days in the hospital were higher among those declaring to suffer at least one chronic disease (Table 3).

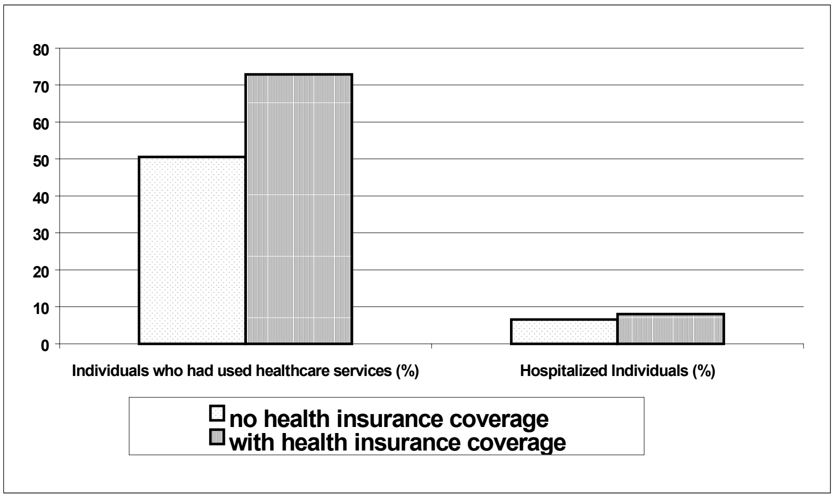
TABLE 3. Percentage of individuals who had used healthcare services, considering the number of chronic diseases[1]

Number of chronic diseases	Individuals who had visited the doctor (%)	Average number of appointments	Hospitalized individuals (%)	Average number of hospitalization days
0	48.14	3.11 (3.5)	4.74	5.22 (11.56)
1	67.66	4.17 (5.0)	9.09	6.98 (16)
2	75.1	5 (6.02)	11.6	7.31 (13.17)
3	82.83	5.81 (6.65)	15.25	7.88 (17.27)
4	87.47	6.99 (8.16)	20.13	7.61 (12.20)
5	90.18	8.27 (9.36)	25.67	8.84 (15.70)
6	92.35	9.61 (11.35)	28.27	10.55 (14.97)
7	95.04	10.92 (12.47)	36.78	9.92 (20)
8	98.15	18.86 (18.37)	48.15	11.42 (20.54)
9	100	18.27 (19.10)	36.36	7.0 (4.16)
Over 10	50	20	0	0

Source: PNAD 98.
1. The figures in parentheses represent the standard deviation.

The health insurance coverage is also relevant for explaining different patterns of access to healthcare services as it may reflect differences in the characteristics of the system's supply. Health insurance plans constitute an alternative to funding services in the sector. Individuals with health insurance coverage tend to use more intensively healthcare services and hospitals, mainly those of better quality. In Brazil, about 24.67% of the people interviewed had health insurance coverage, out of whom 27.35% belong to an institution assisting public servants (denominated public health insurance). Graphic 2 shows that the proportion of individuals using healthcare services was greater among those with health insurance coverage. As for hospitalization, such a difference was not outstanding.

GRAPHIC 2. Proportion of individuals using healthcare services in the presence health insurance coverage



Source: PNAD 98.

4. METHODOLOGY

4.1. The Negative Binomial Hurdle Model

The use of healthcare services presents some relevant characteristics that must be considered when choosing the model to be estimated. Firstly, it can be noted that the number of visits to the doctor and days in the hospital are integers and not negative. The value associated to these variables represents the number of times by which the event had occurred. Secondly, the distribution of such events is similar to the Poisson distribution in which the probability of occurrence of an event is reduced with an increase in its frequency. This means that the proportion of individuals looking for healthcare services decreases with an increase in visits to the doctor or the number of days in the hospital. Thus, these are data concerning the counting of healthcare events.

The Poisson model is the simplest representative of the counting data models. Let us call y_i the number of times the event has occurred, i.e., the number of times the individual i searched for some healthcare service. This model asserts that each y_i is extracted from the Poisson distribution with a positive intensive parameter μ_i. The probability that y_i will occur N times is given by:

$$\Pr(y_i = N) = \frac{e^{-\mu_i}\mu_i^N}{N!}, \qquad (1)$$

where i = 0,1,2,3,........individuals.

It is possible to include explaining variables when it is specified that the intensity parameter μ_i is an exponential function of the covariant set:

$$\mu_i = e^{\left(\sum_{ij} b_j X_{ij}\right)} > 0 \qquad (2)$$

where:

b_j = j-th coefficient;

X_{ij} = j-th explaining variable corresponding to i-th individual.

Thus, the following distribution of number of visits to the doctor or the number of days in the hospital (y_i) is obtained, conditioned to the covariant vector X_i:

$$f(y_i \mid x_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, y_i = 0,1,2,..., \qquad (3)$$

The expected value of this function and the variance are given by:

$$E[y_i \mid x_i] = VAR[y_i \mid x_i] = \mu_i = e^{\left(\sum_{ij} b_j X_{ij}\right)} \qquad (4)$$

The Poisson model may become inadequate for the analysis of the use of healthcare services due to some limitations. Firstly, this model assumes that the intensity parameter μ_{is} is deterministic. Generally speaking, such a supposition is not valid. As seen before, this parameter is a function of the observable characteristics of individuals. However, there are some relevant characteristics which – being unobservable - are not included in the covariant vector. As it is not possible to model such characteristics, it is necessary to include a random term in order to control the unobserved heterogeneity. If such a particularity is neglected, the model may present overdispersion, implying a variance greater than that assumed by the model. Secondly, the events are considered to be independent in this model. In the case of visits to the doctor and days in the hospital, the probability of a current appointment with the doctor may be related to previous visits.

An alternative to this is to use the negative binomial model, which is obtained by assuming that the model intensity parameter has a stochastic component e^{v_i}, where v_i assumes a gamma distribution[21]. If the random component is included, the unobserved heterogeneity is taken into account, as this term reflects the unobservable individuals' characteristics.

[21] See Cameron and Trivedi, 1998, pp.100-102. Gurmu (1997) showed that if there is a malspecification of unobserved heterogeneity distribution, the estimates of parameters will be inconsistent. The author suggests an alternative method of estimation based on semiparametric models. Such models do not impose a specific distribution for the unobserved heterogeneity component.

The negative binomial model is specified as follows:

$$h(y \mid \mu,\alpha)=\frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})\Gamma(y+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\mu+\alpha^{-1}}\right)^{y} \qquad (5)$$

with equal mean and variance[22]:

$$E[y \mid \mu,\alpha]=\mu \qquad (6)$$

$$V[y \mid \mu,\alpha]=\mu(1+\alpha\mu) \qquad (7)$$

where:

α represents the data overdispersion term and $\mu_i = e^{\left(\sum_{ij} b_j X_{ij}\right)} > 0$.

When α=0, the variance is equal to the mean, indicating that there is no data overdispersion. In this case, the model is reduced to the Poisson model.

A third characteristic of healthcare service utilization is that the decision of using such services occurs in two distinct stochastic processes. The first refers to the decision of demanding some medical assistance and the second is related to the frequency of doctor visits, i. e., the number of times the individual used such services after having the first contact. In this case, it is reasonable to assume that the agents determining each of theses processes are distinct. The decision of contacting/searching a healthcare service or not is determined by the patient him/herself and the decision concerning the frequency is, to a great extent, determined by the physician. For this reason, a negative binomial model was estimated in two stages - negative binomial *hurdle* model. In the first stage, a logit model was used to estimate the probability of an individual to look for some healthcare service or to be hospitalized[23]. In the second stage, the truncated at zero negative binomial model (truncated at zero *Negbin*) was used to estimate the expected number of doctor visits and the expected number of days in the hospital, considering only the sub-sample of individuals with positive use of health care services (y_i greater than zero).

The two-stage estimation is crucial to identify which factors affect the individual's behavior in searching for healthcare and which factors determine the provider's behavior when deciding on the amount of care the individual should receive. In the case of hospitalization, in spite of the decisions on hospitalization and the number of days in the hospital be determined by the physician, these two decisions may be viewed as distinct stochastic processes. The physician who decides on whether the individual should be hospitalized may be different from the one who decides on the time the patient should stay in the hospital. The independent variables are expected to affect differently each of these processes.

[22] This variance specification corresponds to the negative binomial model 2 (NB2) which is considered to be a pattern. The variance corresponds to the negative binomial model 1 equal to $(1+\alpha)\mu$.

[23] Cameron and Trivedi (1998) showed that the most general case for estimating the first stage of this hurdle model is through a negative binomial model. Assuming that the overdirpersion parameter α is equal to 1 in the first stage, a logit model is obtained.

For the construction of a negative binomial hurdle, we specified two likelihood functions parametrically independent, each representing a stage in the estimation procedure. Let us call y_i the number of times an individual i looked for the doctor or the number of days of hospitalization, being $y_i \geq 0$ and let d_i be a binary variable which assumes a value equal to 1, when the medical contact is accomplished, and zero when it is not . The likelihood function for the negative binomial hurdle model L_{BN}^{H} may be specified as follows:

$$L_{BN}^{H} = \prod_{i \in \Omega} pr\{y_i = 0 \mid x_i^{'}\beta_1, \alpha_1\}^{1-d_i}\left(1 - pr\{y_i = 0 \mid x_i^{'}\beta_1, \alpha_1\}\right)^{d_i} \times \prod_{i \in \Omega_1} \frac{pr\{y_i \mid x_i^{'}\beta_2, \alpha_2\}}{pr\{y_i \geq 1 \mid x_i^{'}\beta_2, \alpha_2\}} \quad (8)$$

where:

i = 1, 2, 3, ... , individuals;

α_s = overdispersion parameter of data in stages, being s = 1, 2;

Ω = whole sample;

Ω_1 = subsample comprising only individuals who searched for some healthcare service.

The first likelihood function is based on the whole sample Ω, representing the binary process where the individual decides to contact the healthcare service or not. This process is determined by the vector of parameters (β_1, α_1) and estimated through a logit model:

$$\Pr[y_i = 0 \mid X_i] = \frac{1}{\left(1 + e^{\left(\sum_{ij} b_{1j} X_{ij}\right)}\right)} \quad (9)$$

$$1 - \Pr[y_i = 0 \mid X_i] = \frac{e^{\left(\sum_{ij} b_{1j} X_{ij}\right)}}{1 + e^{\left(\sum_{ij} b_{1j} X_{ij}\right)}} \quad (10)$$

The second likelihood function is the truncated at zero negative binomial model. This stage is based only on the sample of individuals that have searched for some healthcare service (Ω_1) and represents the probability that the number of visits to the doctor or hospitalization days be equal to y_i, provided that a contact had been previously made. The following probability is obtained in this stage, determined by the vector of parameters (β_2, α_2):

$$\Pr[y_i \mid X_i, y_i \geq 1] = \frac{\Gamma(y_i + \alpha_2^{-1})}{\Gamma(\alpha_2^{-1})\Gamma(y_i + 1)} \left(\frac{1}{(1 + \alpha_2 \mu_{2i})^{\frac{1}{\alpha_2}} - 1}\right)^{-\alpha_2^{-1}} \left(\frac{\mu_{2i}}{\mu_{2i} + \alpha_2^{-1}}\right)^{y_i} \quad (11)$$

where:

$$\mu_{2i} = e^{\left(\sum_{ij} b_{2j} X_{ij}\right)} > 0$$

The estimates of (β_1,α_1) e (β_2,α_2) are found as the two likelihood functions are separately maximized. If the two processes are identical, i.e., if the two vectors of parameters are equal, the estimation is nested to the standard negative binomial model.

4.2. Specification Tests

We estimated the Poisson model, the negative binomial and the Poisson hurdle in order to test the negative binomial hurdle model. Firstly, we performed the likelihood ratio test to certify whether the data were overdispersed[24]. The following hypotheses were tested:

H_o: $\alpha = 0$

H_1: $\alpha > 0$

The likelihood ratio test is obtained through the difference between the log-likelihood of the Poisson model and the negative binomial:

$$LR = -2\left(LN_{poisson} - LN_{Negbin}\right) \qquad (12)$$

where:

$LN_{poisson}$ = log- likelihood of the Poisson model;

LN_{Negbin} = log-likelihood of the negative binomial model.

When $\alpha = 0$, the negative binomial model is nested to Poisson model and the data are not overdispersed. In this case, the statistics of the likelihood ratio test is equal to zero and the hypothesis H_o is accepted.

Secondly, we tested the negative binomial model against the hurdle negative binomial in order to verify whether the two decision-making processes (the contact decision and the frequency decision) are distinct. The likelihood ratio was used, so that we could test the following hypothesis:

Ho: $\beta_1 = \beta_2$

where:

β_s = vector of parameters of stages, being s = 1,2.

In order to accomplish this test, we estimated the negative binomial model and the hurdle negative binomial so as to obtain the respective log-likelihood. The likelihood ratio test is equal to:

$$LR = 2\left\lfloor LN_{Negbin} - \left(LN_{\log it} + LN_{Negbin-truncado}\right)\right\rfloor \qquad (13)$$

[24] When analyzing the data on frequency of medical visits and hospitalization days, we suspected that the data were overdispersed, since the variance was greater than the mean. We applied the Lagrange multiplier test in order to certify whether the overdispersion was maintained even after including regressors to the model. Another usual test in the literature is that of Wald which is obtained by dividing the estimated value of α, divided by its standard error.

where:

LN_{Negbin} = log-likelihood of the negative binomial model;

LN_{logit} = log-likelihood of the logit model (first stage);

$LN_{Negbin\text{-}truncado}$ = log-likelihood of the truncated at zero negative binomial model (second stage).

If the hypothesis H_o is validated, the hurdle model is reduced to the negative binomial. Thirdly, the Poisson hurdle model was tested against the negative binomial hurdle, by using the likelihood ratio test. Accomplishing such a test is crucial as, when estimating the two stages, the overdispersion of the data in the Poisson model can be eliminated.

4.3. Interpretation of Coefficients

In order to facilitate the interpretation of results, we present odds ratios, estimated by the logistic model, and the marginal effects estimated by the truncated at zero negative binomial model. The odds ratios provide the percentage variation on the probability of the first contact with the healthcare service by the individual due to an increase/reduction in an explaining variable. For example, if the odds ratio estimated for a discrete variable is equal to 1.20, this means that the probability of an appointment with the doctor increases by 20% if the value of this variable is increased in 1 unit. For the binary explaining variables, the odds ratios show the difference in probability of medical visits in relation to the reference category. If the odds ratio estimated for a binary variable is equal to 0.20, the probability of one medical visit at least is 80% lower for this category in relation to the reference group.

In the second stage, the marginal effect of the explaining variable on the use of healthcare services is obtained when the expected value of the truncated at zero negative binomial model related to regressor j-th (x_j) is

$$\frac{\partial E[y \mid x]}{\partial x_j} = \beta_j \exp(x_i^{'}\beta) \qquad (14)$$ differentiated:

This relation shows that an increase (reduction) in the expected number of medical visits is directly proportional to the variation occurred in one of the regressors having in mind that the exp(X'β) is always greater than zero. If the j-th estimated coefficient is equal to 0.12, a 1-unit increase in the explaining variable j implies a proportional increase of 12% in the expected number of medical visits or the number of days in the hospital[25]. In order to evaluate the effect of an explaining binary variable on the expected amount of treatment received by an individual, let us consider a regressor d which assumes the values of 1 or 0 only, and let us suppose that:

$$E[y \mid x_2, d] = \exp(\beta_1 d + x_2^{'}\beta_2) \qquad (15)$$

then:

[25] Cameron and Trivedi (1998) show that it is possible to interpret the coefficients directly, due to the fact that the coefficient βj is equal to a proportional change in the conditional average, if the regressor j th is changed by 1 unit.

$$\frac{E[y \mid d=1, x_2]}{E[y \mid d=0, x_2]}=\frac{\exp(\beta_1 + x_2^{'}\beta_2)}{\exp(x_2^{'}\beta_2)}=\exp(\beta_1) \qquad (16)$$

Thus, the expected number of medical visits and days in the hospital (when the explaining variable d is equal to 1) is $\exp(\beta_1)$ times the expected number of medical visits and hospitalized days, when this variable is equal to zero. Such an effect, measured in percentage terms, is equal to $[\exp(\beta)-1]*100$. A result equal to 3.20 is saying that the expected number of medical visits is 3.20% higher for a category in relation to the reference category.

5. MAJOR RESULTS

Table 4 presents the results of the likelihood ratio test of the Poisson model against the negative binomial. The null hypothesis is rejected, indicating that the number of medical visits and the days in the hospital are overdispersed.

TABLE 4: Test of Data overdispersion
Poisson Model in contrast with the Negative Binomial Model
Ho: α=0 (there is no overdispersion)

Dependent Variable	Total Sample	Occupied Population
Medical Visits	414,971.8	129,599.5
Hospitalization	596,397.3	167,505.2

Source: PNAD/98.

Table 5 shows the results of the specification test of the negative binomial hurdle model against the standard negative binomial and the Poisson hurdle. The tests suggest that the model estimated in two stages is more appropriate. The hypothesis that $\beta_1 = \beta_2$ is rejected, indicating the stochastic process determining the contact decision is different from that determining the frequency decision. Furthermore, the data are overdispersed even after the two-staged estimation.

TABLE 5. Specification Tests of The Negative Binomial Hurdle Model

Models	*Hurdle (NB2)* (LR)			
	Medical Visits		Hospitalization	
	Total Sample	Occupied Population	Total Sample	Occupied Population
Negbin Ho: β_1=:β_2	-13,779.2	-5,837.5	-11,731.6	-3,981.7
Poisson Hurdle	232,505.5	71,.980.8	123,380.0	30,732.3

Source: PNAD/98.

The analysis of major results is presented in the three following subsections which are divided according to the variable groups previously defined[26]. We present the results found for ambulatory services and hospitalization. For each of these kinds of healthcare a model for the whole sample and another for the occupied population at working age were estimated.

5.1. Is there social inequality in the access to healthcare services in Brazil?

The effect of socioeconomic variables on healthcare services is quite differentiated, depending on the kind of service offered. The results reveal social inequality in the access to ambulatory healthcare services in Brazil in favor of more privileged socioeconomic groups, even if morbidity, occupational characteristics and health insurance coverage are controlled. For the inpatient care, the model reveals social inequality in the access which is favorable to less privileged socioeconomic groups. We also observed that the decision of seeing the doctor and the frequency of visits to a physician were responsive to almost all occupational characteristics. The opposite occurs when the hospitalization model is analyzed. The number of worked hours is the only occupational variable that is significant in the first stage estimation. In the second stage, no occupational variables are relevant for explaining the number of days in the hospital.

5.1.1. *Ambulatory services*

The probability of an individual having at least one visit to the doctor increases with income. The odds ratio is equal to 0.73 for the individuals in the first income decile, which implies a 27% lower probability of a medical visit as compared to the probability of those in the last decile. Such a difference between the ninth and the tenth income groups is of 12% only. In the second stage of the model, the coefficients estimated for the income dummies were not significant, indicating that the provider's decision concerning the number of medical visits is not responsive to this variable (Table 6).

TABLE 6. Family Income per Capita – Total Sample
Reference Category: Tenth Decile[1]

Income Groups	Odds Ratio	Truncated at Zero Negbin– Marginal Effect (%)
1st decile	0.73***	4.56*
2nd decile	0.75***	1.35^+
3rd decile	0.76***	0.59^+
4th decile	0.79***	-0.12^+
5th decile	0.78***	0.50^+
6th decile	0.78***	-0.65^+
7th decile	0.82***	-3.84**
8th decile	0.85***	-0.78^+
9th decile	0.88***	-0.97^+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^+$ Nonsignificant.

[26] We did not show results estimated for all explaining variables. A more thorough version can be found in Noronha (2001). The marginal effects can be found in the econometric annex of this paper.

Such a relation between income and access to ambulatory services in Brazil suggests that the barrier encountered by low-income individuals is placed before the contact is made. The provider's behavior, no matter the funding source – public or private - , does not change with the patient's income, but it is the individual's own behavior which is changed. Two hypotheses may be related to this result. The first is concerned with the difference between the expected assistance among both the low and high-income individuals. As they possess a health insurance coverage, the richer individuals always expect to be assisted whenever searching for such services. The poorer individuals, on the other hand, generally show negative expectations about medical assistance, which make them give up searching. Thus, even after controlling for the existence of health plans, richer individuals have better access probably because they search for these services more intensively[27]. The expectation of not being assisted may reflect an unattended demand in the past. If he/she did not manage to be assisted when searching for healthcare services, the individual will prefer not to demand such services any more as he/she expects not to be assisted again.

Another hypothesis is related to the opportunity cost for the people searching for healthcare services which tends to be higher for lower-income classes. Generally speaking, time spent in lines and the cost of shifting to the place of medical assistance in relation to income are higher for the less-privileged socioeconomic groups. Furthermore, the way such income classes are inserted in the market tends to be more precarious, causing a certain employment instability and thus a higher opportunity cost for the search of such services.

When the occupied population is taken into account, one can observe again that the higher the income, the greater the probability of an individual to visit the doctor at least once. The probability of a medical visit is 32% lower for the individuals in the first decile as compared to those in the tenth decile. For those in the ninth decile, this probability is 13% lower. In the second stage, income starts to affect the frequency of medical visits in favor of the more privileged socioeconomic groups. The average number of medical visits is 17% lower for the individuals in the 1st decile and only 7% lower for those in the 8th decile as compared with those in the 10th income decile (Table 7).

TABLE 7. Family Income per Capita – Occupied Population
Reference Category: Tenth Decile[1]

Income Groups	Odds Ratio	Truncated at Zero Negbin Marginal Effect (%)
1st decile	0.68***	-17.07***
2nd decile	0.72***	-11.75***
3rd decile	0.75***	-10.53***
4th decile	0.76***	-16.94***
5th decile	0.78***	-10.40***
6th decile	0.79***	-8.51***
7th decile	0.82***	-12.57***
8th decile	0.84***	-7.09***
9th decile	0.87***	-3.59+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant

[27] The variable health insurance coverage informs only whether individuals are covered or not by some healthcare plan. However, it does not allow us to determine its coverage degree. Thus, even if the healthcare plan existence is controlled, the differences of access amongst the socioeconomic groups may persist also due to the differences in the coverage degree.

This result may be associated to the provider and individual's behavior. On the one hand, the provider may be more inclined to send the patient to other physicians/services, if the patient possesses a higher income level or a healthcare plan. On the other hand, it may be the patient him/herself who decides not to demand other services, because the opportunity cost is higher or because of monetary restrictions. This result is different from the one encountered in the case of the model estimated for the whole sample. When the total population was considered, the most vulnerable population groups in terms of health status – the children and the elderly – who can not postpone healthcare were included.

The family head's education is significant in the two stages of the estimation procedure and the groups with higher education were favored, independently of the age section taken into account. The greater the family head's education degree, the greater the probability of having doctor visits and the greater the expected number of medical visits. Considering the whole sample, one can observe that the probability to see the doctor and the expected number of visits are 43% and 19.73% lower, respectively, for the individuals whose family head is illiterate or has less than a 1-year schooling as compared to those with complete higher learning (Table 8).

TABLE 8. Family Head's Education
Reference Category: Complete Higher Learning[1]

Schooling Groups	**Total Sample**		**Occupied Population**	
	Odds Ratio	Truncated at Zero Negbin– Marginal Effect (%)	*Odds Ratio*	Truncated at Zero Negbin – Marginal Effect (%)
Illiterate. and < less than 1 year	0.57***	-19.73***	0.59***	-17.41***
Incomplete elementary	0.68***	-17.45***	0.69***	-16.86***
Complete elementary	0.70***	-13.87***	0.71***	-13.27***
Incomplete Junior High School	0.76***	-7.02***	0.75***	-8.16***
Complete Junior High School	0.77***	-6.42***	0.74***	-7.86***
Incomplete Senior High School	0.85***	-4.23*	0.83***	-6.08^{+}
Complete Senior High School	0.89***	-3.92**	0.87***	-3.54^{+}
Incomplete Higher Learning	0.93**	-4.59^{+}	0.95^{+}	-6.12^{+}

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

These results suggest that the individual's education level affects not only his/her decision to see the doctor, but the amount of treatment he/she receives. Individuals belonging to families with more educated heads tend to have a better perception of the treatment effect on their health conditions and they may demand for these services more than others. Furthermore, as such individuals are better informed, they tend to better know the specific medical specialties for the needed treatment. Thus, when they are sent to other kinds of medical assistance and if they perceive the importance of such a treatment for their health, these individuals choose to look for such services again.

The family size is significant to explain the contact decision. The higher the number of family members, the smaller the probability that the individual have visited a doctor. In the second stage of the estimation this variable is significant only in the model for the whole sample. The expected number of medical visits is reduced by 3% to the extent that the family size is increased (Table 9).

TABLE 9. Family Size[1]

Estimated Models	Odds Ratio	Truncated at Zero Negbin–Marginal Effect (%)
Total Sample	0.91***	-3.06***
Occupied Population	0.97***	0.02+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

A possible explanation for such a result is that, in a larger family, the parents have acquired a better knowledge of their children's care (learning by doing), taking less recourse to medical services when one of their children gets sick. In addition, the health expense share in the total budget may be smaller in larger families. Thus, even if family income per capita is controlled, the proportion of healthcare expenses may be reduced as the family size increases, implying a smaller utilization of healthcare services.

As for occupational characteristics, we observed that the probability of an individual visit to the doctor is 14.41% greater for those working less than 40 weekly hours and the average number of medical visits is 2.99% higher. Such a result was expected, as the greater the individual's working day, the greater his/her opportunity cost for searching some healthcare service.

The decision to see a doctor is also responsive to the way the individual is inserted in the labor market. For almost all labor categories considered, the probability to see a doctor is smaller than that observed for those regularly employed and such a difference is more remarkable for self-employed workers (31%), unregistered workers (25%), and home servants (25%). In the second stage of the model, we observed that the expected number of visits was smaller only for the unregistered workers. The medical visit frequency is 9.26% smaller for such individuals, as compared to the frequency of formal workers (registered) (Table 10). These results show that the more precarious the insertion of individuals in the labor market, the higher their opportunity cost of looking for a doctor.

TABLE 10. Position in the Occupation
Reference Category: formal sector employee[1]

Position in the Occupation	Odds Ratio	Truncated at Zero Negbin - Marginal Effect (%)
Military and Public Servant.	0.94*	-2.87+
Unregistered Sector Worker	0.75***	-9.26***
Home Servant	0.75***	-3.49+
Self-employed Worker	0.69***	-3.25+
Employer	0.83***	-5.60+
Own-consumption Worker	0.79***	-3.81+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

5.1.2. *Inpatient Care*

The most important socioeconomic indicator for explaining access to inpatient care is the family income per capita. The estimated results show that there is social inequality in the country in the access to inpatient care which is favorable to the poorer. This can be verified only when the estimated model for the whole sample is considered[28]. The probability of an individual belonging to the first decile be hospitalized is 76.6% higher than the chance of an individual in the tenth decile and 9% higher for those in the sixth income group. In the second stage of the estimation, income is again favorable to the poorer. The average number of days in the hospital is 30%, 31% e 41% higher for individuals in the first three deciles, respectively, as compared to the highest income group (Table 11). This result seem to reflect the fact that the poorer search for some healthcare when their health conditions are worsened thus needing a more intensive treatment. In spite of the fact that the model controls for morbidity measures, such variables may not be totally reflecting the treatment needs of low-income groups and the disease severity, specially for the most vulnerable age groups: the children and the elderly.

TABLE 11. Family Income per Capita
Reference Category: Tenth Decile[1]

Income Groups	Total Sample		Occupied Population	
	Odds Ratio	Truncated at Zero Negbin - Marginal Effect (%)	Odds Ratio	Truncated at Zero Negbin–Marginal Effect (%)
1st decile	1.76***	29.83***	1.26***	15.38+
2nd decile	1.51***	31.12***	1.20**	17.76+
3rd decile	1.30***	41.47***	0.96+	44.74***
4th decile	1.23***	18.09**	1.01+	-0.52+
5th decile	1.11***	32.52***	0.98+	20.48*
6th decile	1.09**	18.24**	0.95+	17.53+
7th decile	1.01+	25.21***	0.90*	24.47**
8th decile	0.99+	22.96***	0.96+	10.86+
9th decile	0.95+	21.13**	0.89**	22.56**

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant

The access to hospital services is not so responsive to the other socioeconomic variables. As for occupational characteristics, only the number of worked hours is significant in the first stage of the model. Individuals working less than 40 weekly hours show a 7% higher probability to be hospitalized than those working full time. In the second stage, none of these variables were relevant to explain the number of days in the hospital.

[28] The income was not significant in the two stages of the model, when the analysis was restricted to individuals between 15 and 65 years of age.

5.2. Access to healthcare services, according to the supply characteristics

5.2.1. *Ambulatory services*

Taking the estimated model for the whole sample into account, the probability of a medical visit is 91% larger for the individuals with a public healthcare institution plan and 139% higher for those having some private health insurance coverage. In the second stage, the expected numbers of medical visits are 24.37% and 38.65% higher for individuals covered by healthcare plans provided by the public and private sectors, respectively (Table 12).

TABLE 12. Supply Characteristics[1]

Variables	Total Sample		Occupied Population	
	Odds Ratio	Negbin Truncated at Zero –Marginal Effect (%)	*Odds Ratio*	Negbin Truncated at Zero –Marginal Effect (%)
Place of Residence – Reference category: Rural	1.21***	17.63***	1.08***	0.95^{+}
Public servant's healthcare plan	1.91***	24.37***	1.90***	25.61***
Private healthcare plan	2.39***	38.65***	2.39***	41.60***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

The significance of such variable reflects a segmentation observed in the Brazilian healthcare system. Individuals covered by some healthcare plan have access to a wide variety of healthcare services of good quality and at a low cost.

Living in an urban area affects the individual's decision to see the doctor and the amount of treatment he/she receives. In the two stages of the estimated model for the whole sample, individuals living in urban areas show a 21% higher probability to visit the doctor and the expected number of medical visits is 17.63% higher (Table 12). This reflects the scarcity of such services in rural areas and individuals living in the countryside will find greater difficulty in the access to some medical treatment. This variable is not significant for the occupied population.

5.2.2. *Hospitalization services*

The estimated results for the whole sample show that the probability of hospitalization is 47% higher for those having some public healthcare plan and 53% higher for those with some private healthcare plan. In the second stage, we observed that the individuals hospitalized by SUS stayed longer in the hospital and the expected number of days in the hospital being 25.33% higher (Table 13). This suggests that the insurance companies impose more stringent restrictions than SUS as for the number of days individuals must stay in the hospital for each accomplished medical procedure.

Table 13. Supply Characteristics[1]

Variables	Total Sample		Occupied Population	
	Odds Ratio	Negbin Truncated at Zero –Marginal Effect (%)	*Odds Ratio*	Negbin Truncated at Zero – Marginal Effect(%)
Place of Residence – Reference Category: Rural	1.04*	19.23***	0.97^{+}	8.97^{+}
Public servant's health insurance coverage	1.47***	-	1.54***	-
Private health insurance coverage	1.53***	-	1.66***	-
Individuals hospitalized by SUS	-	25.33***	-	37.42***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

For individuals living in urban areas, the probability to be hospitalized is 4% higher (at 10% of significance) and the expected number of days in the hospital is 19.23% higher than for those living in rural areas. This result can be verified when the estimated model for the whole sample is analyzed. This variable is not significant for the occupied (Table 13).

5.3. Access to healthcare services, according to the needs

Access to services of medical visits is quite responsive to the variables of needs. In all health indicators used, the probability of medical visits and the expected number of medical visits are higher for those less healthy individuals. This result can be verified, depending on the considered age group.
The result was slightly differentiated for hospitalization services. If the whole sample is considered, measures of needs were significant to explain the probability of an individual be hospitalized, being higher for those in worse health conditions. In the second stage, the expected number of days in hospital is responsive to only two health indicators – restriction to physical activity, due to health reasons in the reference period, and self-assessed health status, indicating that the less-healthy individuals tend to stay longer in the hospital.

When the analysis is restricted to the occupied population, it was possible to include a variable measuring the degree of difficulty people have in accomplishing some habitual tasks. We were able to observe that the greater the difficulty in accomplishing these tasks, the greater the probability of an individual to be hospitalized and the longer the treatment period. Another important variable to explain access to healthcare services was the proportion of individuals having their activities limited in the two weeks previous to the survey. The probability to be hospitalized and the number of days in the hospital were higher for those having some restriction in their activities. The other morbidity variables were significant only in the first stage of the estimation procedures.

6. FINAL REMARKS

The major contribution of this paper is its analysis of the social inequality in the access to healthcare services in Brazil as two distinct stochastic processes. The estimation of the negative binomial hurdle model is relevant, as it permits to evaluate whether the inequality in this market is related to the individuals' behavior when demanding healthcare services or the doctor's behavior when deciding on the intensity of treatment the patient should receive.

The results encountered for ambulatory services show that there is inequality in the access to healthcare services in Brazil, favoring the more privileged income groups. This result suggests that the barrier found by the low-income individuals occurs even before any contact is established. The variables related to the occupational characteristics are also relevant to explain access to medical assistance. The probability of seeing a doctor and the expected number of medical visits are smaller for those individuals working full time than for those working less than 40 weekly hours. This finding is also observed for individuals whose insertion in the labor market is more precarious, mainly for those working in the informal market, reflecting a higher opportunity cost that these people face when demanding some healthcare service.

As for hospitalization services, we observed that the smaller the individual's income, the greater the probability of seeing a doctor. The frequency of medical visits is responsive to income when the model is estimated for the whole sample, again favorable to the poorer groups.

Such results, however, are not conclusive. There are still some restrictions found in the model which need to be evaluated so as to obtain more precise results. An extension of this paper would be to evaluate inequality in the access to healthcare services in Brazil, by considering some explaining variables as being endogenous. An example of this is the self-assessed health status. People more frequently assisted by a physician are better informed on their health status. Thus, they tend to better evaluate their health status as compared to those not demanding such services. As a result, the assessment of health status depends on the use of healthcare services and these, in turn, are affected by the individuals' health status.

There are also two hypotheses posed by the negative binomial hurdle model which must be tested. Firstly, the negative binomial model considers that the unobserved heterogeneity assumes gamma distribution. An alternative is to estimate the hurdle model for all the counting data of events by means of the semiparametric estimation method which does not impose a specific distribution for the unobserved heterogeneity.

Another hypothesis of the hurdle model is that the individuals had only one disease event during the observation period considered in the database. Thus, the first count was equivalent to the first contact with the physician and the remaining counts were equivalent to medical visits related to this very event. The problem concerning this hypothesis is that it may have occurred more than one disease event implying multiple first contacts.

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ECONOMETRIC ANNEX

1. AMBULATORY SERVICES – ESTIMATED MODEL FOR TOTAL SAMPLE

Table 1. Family Composition
Reference Category: other kind of family and couple or mother whose children's age was undeclared [1]

Family Composition	Odds Ratio	Negative Binomial Truncated at Zero - Marginal Effect (%)
Families composed only by the couple	1.23***	12.95***
Couples with children <14	1.66***	27.62***
Couples with children >14	1.13***	10.49***
Couples with children <14 and >14	1.21***	75.89***
Mothers with children <14	1.56***	20.56***
Mothers with children >14	1.09***	12.34***
Mothers with children <14 and > 14	1.06**	2.27+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 2. Demographic Variables [1]

Variables	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Race – Reference category: Non-whites	1.04***	-0.88+
Sex – Reference category: Females	0.57***	-23.89***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 3. Self-Assessed Health Status
Reference Category: Very Poor [1]

Self-Assessed Health Status	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect(%)
Very Good	0.42***	-68.47***
Good	0.60***	-62,41***
Regular	1.17**	-40.25***
Poor	1.39***	-14.94***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 4. Other Morbidity Variables [1]

Variables	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Number of Chronic Diseases	1.54***	17.21***
Restricted activities in the two previous weeks for health reasons	3.62***	45.55***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

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Table 5. Federative Units
Reference Category: São Paulo[1]

Federative Units	Odds Ratio	Negative Binomial Truncated at Zero - Marginal Effect (%)
Maranhão	0.67***	-0.56***
Piauí	0.97+	-0.48***
Ceará	1.14***	-0.23***
Rio Grande do Norte	1.16***	-0.14***
Paraíba	0.95+	-0.21***
Pernambuco	1.16***	-0.04**
Alagoas	0.84***	-0.12***
Sergipe	1.04+	-0.34***
Bahia	1.13***	-0.17***
Minas Gerais	1.11***	-0.13***
Espírito Santo	1.40***	-0.08***
Rio de Janeiro	0.94***	0.001+
Paraná	1.04**	-0.06***
Santa Catarina	0.71***	-0.32***
Rio Grande do Sul	1.02+	0.03*
Mato Grosso do Sul	1.09***	-0.25***
Mato Grosso	0.76***	-0.51***
Goiás	0.96+	-0.37***
Distrito Federal	1.16***	-0.006+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant

2. AMBULATORY SERVICES – ESTIMATED MODEL FOR INDIVIDUALS AGED 15 - 65

Table 6. Family Composition
Reference Category: other kind of family and couple or mother whose children's age is undeclared [1]

Family Composition	Odds Ratio	Negative Binomial Truncated at Zero - Marginal Effect(%)
Families composed by the couples alone	1.17***	11.77***
Couples with children <14	1.22***	17..2***
Couples with children >14	0.98+	3.09+
Couples with children <14 and >14	1.12***	5.03+
Mother with children <14	1.08**	13.58***
Mother with children >14	0.95+	2.98+
Mother with children <14 and > 14	0.94+	2.67+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 7. Branches of Activity
Reference Category: Agricultural Activity[1]

Branches of Activity	Odds Ratio	Negative Binomial Truncated at Zero - Marginal Effect (%)
Manufacturing	1.23***	15.66***
Civil construction	1.12***	15.17***
Other industrial activities	1.29***	16.60***
Commerce	1.09***	15.33***
Services	1.12***	17.12***
Economic activity	1,26***	12,72***
Transport and communications	1.14***	16.63***
Social activities	1.17***	12.89***
Public administration	1,28***	28,04***
Other activities	1.24***	24.32***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 8. Other socioeconomic and Demographic Variables [1]

Variables	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Race – Reference category: non-whites	1.02+	-2.80**
Sex – Reference category: females	0.42***	-35.43***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 9. Self-Assessed Health Status
Reference Category: Very Poor[1]

Self-Assessed Health Status	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Very Good	0.40***	-64.45***
Good	0.55***	-57.33***
Regular	0.95+	-36.13***
Poor	1.17+	-12.80*

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 10. Other Morbidity Variables[1]

Variables	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Number of Chronic diseases	1.40***	13.40***
Restricted activities in the previous two weeks for health reasons	3,69***	48,45***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 11. Degree of Physical Mobility
Reference Category: No difficulty at all[1]

Degree of Physical Mobility	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Unable	1.68***	65.00***
Great Difficulty	1.55***	37.78***
Little Difficulty	1.43***	16.99***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 12. Federative Units
Reference Category: São Paulo[1]

Federative Units	Odds Ratio	Negative Binomial Truncated at Zero – Marginal Effect (%)
Maranhão	0.85***	-40.65***
Piauí	1.08+	-36.06***
Ceará	1.22***	-15.06***
Rio Grande do Norte	1.27***	-10.72**
Paraíba	1.09*	-12.30**
Pernambuco	1.24***	0.41+
Alagoas	0.90*	-6.76+
Sergipe	1.25***	-20.69***
Bahia	1.32***	-9.99***
Minas Gerais	1.21***	-7.97***
Espírito Santo	1.55***	0.02+
Rio de Janeiro	0.94**	1.47+
Paraná	1.14***	-0.44+
Santa Catarina	0.80***	-22.81***
Rio Grande do Sul	1.16***	7.81***
Mato Grosso do Sul	1.25***	-15.70***
Mato Grosso	0.93+	-35.41***
Goiás	1.10***	-27.33***
Distrito Federal	1,23***	-3.09+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant

3. HOSPITALIZATION SERVICES - MODEL ESTIMATED FOR THE TOTAL SAMPLE

Table 13. Education of Family Head
Reference Category: Complete Higher Learning[1]

Schooling Groups	*Odds Ratio*	Negative Binomial Truncated at Zero - Marginal Effect (%)
Illiterate and < 1 year at school	0.93+	-18.18*
Incomplete elementary school	0.94+	-20.72**
Complete elementary school	0.98+	-17.28*
Incomplete junior high school	1.06+	-15.36+
Complete junior high school	1.02+	-14.24+
Incomplete senior high school	1.05+	-9.74+
Complete senior high school	1.00+	-17.09*
Incomplete higher learning	1.00+	-22.43*

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 14. Family Composition
Reference Category: other kind of family and couple or mother whose children's age is undeclared [1]

Family Composition	Odds Ratio	Negative Binomial Truncated at Zero – Marginal Effect (%)
Families only composed by the couples	1.22***	-10.38+
Couples with children <14	1.95***	-21.48***
Couples with children >14	1.05+	-9.27+
Couples with children <14 and >14	1.04+	-18.44**
Mother with children <14	1.87***	-12.64+
Mother with children >14	0.99+	0.34+
Mother with children <14 and > 14	0.99+	-8.61+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 15. Other Socioeconomic and Demographic Variables [1]

Variables	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Number of family members	0.94***	0.83+
Race – Reference category: non-whites	1.04**	-10.52***
Sex – Reference category: females	0.63***	32.14***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 16. Self-Assessed Health Status
Reference Category: Very Poor[1]

Self-Evaluated Health Status	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Very Good	0.22***	-53.02***
Good	0.30***	-47.87***
Regular	0.53***	-32.11***
Poor	0.87**	-11.36+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 17. Other Morbidity Variables[1]

Variables	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Number of chronic diseases	1.16***	1.67+
Restricted activities	2.58***	18.86***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 18. Major Hospital Treatment Received
Reference Category: General Clinic Treatment[1]

Treatment Received	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect(%)
Normal Birth	-	-60.67***
Cesarean	-	-29.23***
Surgery	-	6.83+
Psychiatric	-	389.25***
Examinations	-	-47.80***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 19. Federative Units
Reference Category: São Paulo[1]

Federative Units	Odds Ratio	Negative Binomial Truncate at Zero - Marginal Effect (%)
Maranhão	1.04+	-39.11***
Piauí	0.97+	-38.70***
Ceará	0.98+	-12.99+
Rio Grande do Norte	1.18***	-27.33***
Paraíba	1.11**	-21.34**
Pernambuco	0.90***	-4.21+
Alagoas	0.77***	-13.89*
Sergipe	0.99+	-10.56+
Bahia	0.88***	-25.09***
Minas Gerais	1.07**	-10.44*
Espírito Santo	1.14**	-17.33+
Rio de Janeiro	0.75***	31.55***
Paraná	1.21***	-9.25+
Santa Catarina	1.18***	0.70+
Rio Grande do Sul	1.09***	15.62**
Mato Grosso do Sul	1.19***	-21.71**
Mato Grosso	1.28***	-31.67***
Goiás	1.39***	-26.33***
Distrito Federal	0.94+	-14.64*

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

4. HOSPITALIZATION SERVICES - MODEL ESTIMATED FOR INDIVIDUALS AGED 15 - 65

Table 20. Education of Family Head
Reference Category: Complete Higher Learning[1]

Schooling Groups	Odds Ratio	Negative Binomial Truncated at Zero - Marginal Effect (%)
Illiterate and < 1 year at school	1.00^{+}	-2.58^{+}
Incomplete elementary school	0.97^{+}	-9.48^{+}
Complete elementary school	1.03^{+}	-2.69^{+}
Incomplete junior high school	1.05^{+}	-14.43^{+}
Complete junior high school	1.08^{+}	-13.13^{+}
Incomplete senior high school	1.00^{+}	-15.29^{+}
Complete senior high school	1.09^{+}	-13.94^{+}
Incomplete higher learning	1.04^{+}	-33.20***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

Table 21. Family Composition
Reference Category: other kind of family and couple or mother whose children's age is undeclared [1]

Family Composition	Odds Ratio	Negative Binomial Truncated at Zero - Marginal Effect (%)
Families only composed by the couples	1.09^{+}	-25.71**
Couples with children <14	1.63***	-24.95**
Couples with children >14	0.94^{+}	-15.52^{+}
Couples with children <14 and >14	0.97^{+}	-11.11^{+}
Mother with children <14	1.87***	-25.64**
Mother with children >14	0.84**	-16.41^{+}
Mother with children <14 and > 14	0.93^{+}	-12.81^{+}

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

Table 22. Occupational Position
Reference Category: formal employee[1]

Occupational Position	Odds Ratio	Negative Binomial Truncated at Zero - Marginal Effect (%)
Military and public servants	0.91^{+}	-7.29^{+}
Informal sector employees	0.92*	-15.92**
Home servant	0.98^{+}	-9.50^{+}
Self-employed workers	0.98^{+}	-12.99^{+}
Employers	1.16**	18.89^{+}
Own-consumption worker	0.99^{+}	-3.14^{+}

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

Table 23. Branches of Activity
Reference Category: Agricultural Activity[1]

Branches of Activity	Odds Ratio	Negative Binomial Truncated at Zero - Marginal Effect (%)
Manufacturing	0.89*	4.77^{+}
Civil construction	0.89*	31.10**
Other industrial activities	1.05^{+}	4.61^{+}
Commerce	0.95^{+}	25.93**
Services	0.84***	21.56^{+}
Economic activity	0.96^{+}	25.87^{+}
Transport and communications	0.94^{+}	6.93^{+}
Social activities	1.05^{+}	20.53^{+}
Public administration	1.21**	45.99**
Other activities	0.77**	14.83^{+}

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

Table 24. Demographic Variables [1]

Variables	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Number of family members	0.99^{+}	-2.15^{+}
Race – Reference category: non-whites	0.99^{+}	-12.12***
Sex – Reference category: females	0.52***	48.43***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

Table 25. Self-Assessed Health Status
Reference Category: Very Poor[1]

Self-Evaluated Health Status	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Very Good	0.36***	-15.72^{+}
Good	0.45***	-5.63^{+}
Regular	0.72**	6.13^{+}
Poor	1.11^{+}	-0.01^{+}

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

Table 26. Other Morbidity Variables[1]

Variables	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Number of chronic diseases	1.10***	1.46^{+}
Restricted activities in the two previous weeks for health reasons	2.60***	26.17***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, $^{+}$ Nonsignificant.

Table 27. Degree of Physical Mobility
Reference Category: No difficulty at all[1]

Degree of Physical Mobility	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Unable	2.35***	75.80***
Great difficulty	1.62***	54.72***
Little difficulty	1.38***	37.96***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 28. Major Hospital Treatment Received
Reference Category: General Clinic Treatment[1]

Treatment Received	Odds Ratio	Negative Binomial Truncated at Zero –Marginal Effect (%)
Normal birth	-	-37.82***
Cesarean	-	3.98+
Surgery	-	16.32**
Psychiatric	-	374.38***
Examinations	-	-42.32***

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.

Table 29. Federative Units
Reference Category: São Paulo[1]

Federative Units	Odds Ratio	Negative Binomial Truncated at Zero – Marginal Effect (%)
Maranhão	0.92+	-31.59***
Piauí	0.90+	-27.24*
Ceará	0.89*	-8.50+
Rio Grande do Norte	1.03+	-40.67***
Paraíba	0.96+	-40.98***
Pernambuco	0.87**	-4.21+
Alagoas	0.70***	9.01+
Sergipe	1.13+	13.14+
Bahia	0.87**	-23.02**
Minas Gerais	1.00+	-14.66+
Espírito Santo	1.17*	-3.01+
Rio de Janeiro	0.74***	28.01*
Paraná	1.15**	-7.47+
Santa Catarina	1.21***	7.28+
Rio Grande do Sul	1.04+	16.86*
Mato Grosso do Sul	1.32***	-21.17*
Mato Grosso	1.42***	-20.86+
Goiás	1.37***	-32.10***
Distrito Federal	0.97+	-10.02+

1. *** Significant at 1%, ** Significant at 5%, * Significant at 10%, + Nonsignificant.