World Economics Association
Conferences, 2014
Is a more inclusive and sustainable development possible in Brazil?
2014, n. 1: 5th May – 20th July

Title of paper: Measurement and determinants of inequalities in healthcare utilization: an analysis for the Brazilian regions

Jacqueline N. Cambota and Fabiana F. Rocha

Abstract:

The aim of this paper is to measure and explain income-related inequality in healthcare utilization for Brazilian regions. Firstly, inequality was estimated by two measures: concentration index and horizontal inequality index. The first index reflects income-related inequalities, but does not distinguish the differences in utilization by healthcare needs. The horizontal inequality index, in turn, measures income-related inequality among individuals with similar needs. Thus, the results indicate horizontal pro-rich inequity in the utilization of doctor visits and a greater degree of inequity in the North and Northeast of Brazil. On the other hand, there is no evidence of inequity in hospital care utilization. Then, we proceeded to the decomposition of inequality based on utilization determinants. The results of the decomposition analysis showed that contributions of need determinants are mostly pro-poor and that contributions of social determinants are more diversified. Income, education, and health insurance contributed to increasing the pro-rich distribution of doctor visits and reducing the distribution of pro-poor inpatient care, while activity status contributions were mostly pro-poor because the opportunity cost of seeking healthcare is higher among economically active people.

Keywords: Healthcare utilization. Horizontal inequity. Decomposition.

Authors details:

Jaqueline Cambota Technical Office for Economic Research of Northeast, Bank of Northeastern Brazil, 5700 Pedro Ramalho Ave, Passare, Zip Code: 60743-902. Fortaleza, CE, Brazil.

Fabiana Rocha. University of Sao Paulo, 98 Prof. Luciano Gualberto Ave, Cidade Universitaria, Zip Code: 05508-900. Sao Paulo, SP, Brazil, E-Mail:frocha@usp.br.

1. Introduction

The decrease in income inequality in Brazil achieved in the past decade allowed millions of Brazilians to lift out of poverty, but inequality has persisted in several other areas. Overcoming inequalities in the delivery of healthcare continued to be a challenge despite the fact that universal, equitable and integral access to health services for the whole Brazilian population has existed since the Federal Constitution of 1988.

Evidence that healthcare utilization in Brazil has been marked by social inequalities [1-10] shows that equity in healthcare utilization must still go a long way before it is actually attained. More than that, the evidence indicates that, historically, these inequalities are reinforced by regional disparities in the distribution of physical and human resources and by the unequal distribution of regional income.

The decentralized delivery of healthcare in Brazil, characterized by the shared participation of each sphere of government (federal government, states, and municipalities) in the supply and financing of health services, contributes to an unequal supply amongst Brazilian states, because poorer regions cope with larger difficulties in fulfilling their role in the financing and supply of health services.

Unequal regional income distribution poses a greater challenge for those who live in poorer regions, where the supply of public health services is smaller, and those who cannot afford to pay for complementary health insurances. Therefore, unequal regional income distribution proves a greater hindrance to the purchase of healthcare coverage by the poorer population in these regions.

Despite the regulatory measures for increasing the efficiency and reduction of inequalities, the delivery of health services continued to be extremely unequal across Brazil, both socioeconomically and geographically speaking [2]. As pointed out by [11], how much the larger the inequality in income distribution, the more unlikely it will be for an individual to have a good health status in Brazil.

The Brazilian literature shows that the utilization of health services that access to healthcare in Brazil is strongly influenced by the socioeconomic background and by the place of residence, as richer people living in more developed regions have better access to healthcare than those who are poorer and live in less developed regions.

However, few studies are concerned with measuring the degree of such inequalities and explaining their determinants. Thus, this paper assesses equity in the delivery of healthcare across

Brazilian regions by determining the degree of income-related inequality in healthcare utilization and decomposing its determinants.

The data consist of information obtained from the Brazilian National Household Survey (PNAD) for 2008, which includes a health supplement containing annual data and questions on the health of the surveyed individuals. Given that PNAD has a complex sampling design, it was necessary to use a bootstrapping procedure for complex samples to obtain the estimates of standard errors of the concentration indices and of the contribution of inequality determinants. If this design had been overlooked, the variance could have been biased and the significance of parameters would also have been affected.

Aside from this introduction, the paper is organized into five sections. Section 2 presents the measures initially used to determine the inequalities in healthcare utilization and describes the methods for the measurement of social inequalities in the delivery of healthcare referenced in the most recent literature and which will be used for the empirical analysis. Section 3 describes the decomposition of inequality determinants. Section 4 presents the database and defines the utilization, need and social variables. Section 5 discusses the empirical method and the procedure for statistical inference in complex samples such as in the PNAD. Section 6 shows the results for social inequalities from a regional perspective and the decomposition of inequality into need and social determinants, of which the latter is deemed to be the major contributing factor for unfair inequalities or inequities. Finally, Section 7 concludes.

2. Measurement of social inequalities (inequities) in healthcare utilization

The concentration in health variables is basically assessed by three measures: slope index of inequality (SII), relative index of inequality (RII) and concentration index (CI). Only these indices meet the minimum requirements for measuring social inequalities in healthcare utilization by: (i) reflecting the socioeconomic dimension of health inequalities; (ii) using information on all population groups; and (iii) being sensitive to changes in the distribution of the population across socioeconomic groups. Nevertheless, if one is interested in comparisons between geographical units or over time, the visual representation as deviations from equality provides the CI with an additional advantage [12].

Owing to this advantage and because it is easily calculated by a "convenient regression," corresponding to the transformation of the health variable on the fractional rank[1] of the classification

[1] Before estimating $\hat{\beta}_1$, it is necessary to calculate the fractional rank variable, defined as

$$r_i = \sum_{j=0}^{i-1} \omega_j + \frac{\omega_i}{2} \qquad (2.2)$$

The fractional rank of the socioeconomic status is defined by equation (2.2), where ω_i is defined as the sample weight scaled to sum 1, with observations in increasing order of socioeconomic distribution, and $\omega_0 = 0$.

variable of the socioeconomic status, the CI is found at a higher frequency in the literature on inequalities in healthcare utilization, and is calculated by the following convenient regression:

$$\frac{2\sigma_r^2}{\bar{y}} y_i = \alpha_1 + \hat{\beta}_1 r_i + \varepsilon_i \tag{2.1}$$

Where coefficient $\hat{\beta}_1$ stands for the CI, y_i is the health variable of interest, $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ is the mean of this variable, r_i is the fractional rank of the classification variable of socioeconomic status, and σ_r^2 is the variance of the variable (r).

If the health variable is equally distributed across the socioeconomic groups, the CI will be equal to zero. However, if it is concentrated in the hands of the most socioeconomically disadvantaged, the CI will take on the lowest value (-1); on the other hand, if it is concentrated in the hands of the least socioeconomically disadvantaged, the CI will take on the highest value (1).

Nonetheless, healthcare utilization varies according to the individual needs determined by demographic and morbidity characteristics. Therefore, the inequality estimated from equation (2.1) may be capturing differences in these variables, requiring the standardization of the CIs on the basis of utilization needs. This alone will allow obtaining a measure of inequality that reflects only the inequalities related to socioeconomic background. In brief, the standardization yields a measure of inequity that allows assessing inequalities in healthcare utilization for individuals with the same health needs.

The first step for the construction of this measure is to estimate the demand for health services. By assuming a model with a linear explanatory variable, we have:

$$y_i = \alpha_1 + \beta_1 lninc_i + \sum_j \delta_j x_{j,i} + \sum_k \gamma_k z_{k,i} + \varepsilon_i \tag{2.3}$$

Where the dependent variable, y_i, is a variable of healthcare utilization (number of doctor visits; number of hospital admissions, for instance) and the explanatory variables are split into three types: logarithm of the household income of individual i $(lninc_i)$, a set of j variables of need (x_j), demographic and morbidity characteristics, and a set of k variables (z_k) that represent the social determinants of inequality in healthcare utilization as they are correlated with healthcare use and the rank variable of income distribution.

The logarithm of income indicates a concave relationship between income and health, i.e., health tends to grow with income, but at decreasing rates. The vector x_j contains the variables that should be used for standardization, whereas the vector z_k includes those variables that should not be used for standardization, but that ought to be controlled so as to avoid a possible bias towards the coefficients of the need variables. α_1, β_1, δ_j and γ_k represent the parameters to be estimated, while ε_i corresponds to the error term.

Equation (2.3) generates the need-predicted values, i.e., the expected use of individual i based on his/her need characteristics. By combining the estimates of the coefficients obtained from this equation with the observed values of $x_{j,i}$ and with the sample means of $lninc_i$ and of z_k, we get the "x-expected" need values:

$$\hat{y}_i^X = \hat{\alpha}_1 + \hat{\beta}_1 lninc_i{}^m + \sum_j \hat{\delta}_j x_{j,i} + \sum_k \hat{\gamma}_k z_{k,i}{}^m \qquad (2.4)$$

This value indicates the amount of healthcare an individual ought to be provided with if he/she were treated like the other individuals who, on average, have the same characteristics. The estimate of need-standardized use, $\hat{y}_i^{IS}$, necessary to calculate the inequity index, is obtained as the difference between actual use and "x-expected" use plus the mean of the observed y_i:

$$\hat{y}_i^{IS} = y_i - \hat{y}_i^X + \bar{y} \qquad (2.5)$$

The predicted value of need-standardized use ($\hat{y}_i^{IS}$) is then used to obtain the horizontal inequity index (HIwv) [13]. This measure is calculated the same way as the unstandardized CI and is interpreted likewise: a positive value indicates horizontal inequity in utilization in favor of wealthier individuals; a negative value represents inequity in utilization in favor of the poorer; a null or insignificant value indicates lack of inequity, i.e., utilization and needs are proportionally distributed in the income distribution.

3. Decomposition of inequality in healthcare utilization

To explain the inequalities in healthcare utilization measured by the CI, inequality is broken down into utilization determinants, following [14] and [15].[2]

By supposing that healthcare utilization follows a linear model as described in (2.3), [16] demonstrate that the CI can be decomposed into:[3]

$$CI = \eta_r CI_{lninc} + \sum_j \eta_j CI_{x,j} + \sum_k \eta_k CI_{zk} + CI_\epsilon / \bar{y} \qquad (3.1)$$

Where CI_{lninc} is the income concentration index, $CI_{x,j}$ is the concentration index established for x_j, CI_{zk} is the concentration index for $z_{k,i}$ and CI_ϵ is the generalized concentration index of the error term ε. These indices are computed according to equation (2.1).

Equation (3.1) shows that the concentration index of healthcare utilization consists of: i) a deterministic component given by the weighted average of the CIs of k regressors (income, need

[2] The decomposition of the concentration index of healthcare utilization was previously applied by [16] to analyze the causes of malnutrition in Vietnam.

variables and other socioeconomic variables; in which the weight is simply the elasticity of y in relation to the explanatory variable; and ii) a residual component that reflects inequality in healthcare utilization that cannot be explained by systematic variations in explanatory variables across income groups.

The elasticities of the health need variables, for instance, are defined as:

$$\eta_j = \delta_j x_j^m / y^m \tag{3.2}$$

Where δ_j is the coefficient of the linear regression, y^m is the weighted average of y and x_j^m is the weighted average of x_j. These elasticities denote the percentage change in y resulting from a percentage change in x_j. The elasticities of the logarithm of income and of the set of non-need variables, z_k, are defined analogously.

The problem with the application of the linear approach to the decomposition of inequality in healthcare utilization arises from the fact that the measures of use often yield whole and nonnegative values. This is the case, for example, of the number of doctor visits and the number of hospital admissions, which makes the use of nonlinear models more appropriate than the linear model described in equation (2.6). A general form for these models can be written as:

$$y_i = G\left(\beta_1 lninc_i + \sum_j \delta_j x_{j,i} + \sum_k \gamma_k z_{k,i}\right) + \varepsilon_i \tag{3.3}$$

Although the decomposition is not directly applied to equation (3.3), the representation by linear approximation allows restoring the decomposition framework defined in equation (3.1) by the representation of marginal effects at the mean. To do that, we define an approximation to a linear model of utilization such as:

$$y_i = \beta_1^m lninc_i + \sum_j \delta_j^m x_{j,i} + \sum_k \gamma_k^m z_{k,i} + \varepsilon_i \tag{3.4}$$

Where β_1^m is the partial income effect, δ_j^m and γ_k^m are the partial effects for the need and non-need factors, respectively.

4. Database and definition of the variables

The Brazilian National Household Survey (PNAD) is aimed at collecting information on the socioeconomic characteristics of the Brazilian population, being annually[4] conducted in all states. Some topics are regularly addressed while others are included according to the need of information and are dealt with at a variable frequency in supplements, for which data on the access to healthcare utilization and health status are collected jointly with the Brazilian Ministry of Health every five years since 1998.

The utilization of doctor visits is addressed in the questions “Have you seen a doctor in the past 12 months?” and “How many times have you seen a doctor in the past 12 months?.” The former

[4] Except for the years in which the Census was carried out.

question informs about the probability of initial contact for medical care whereas the latter provides the frequency of medical care. The sum of these questions gives a measure of overall utilization, including those individuals who did not seek any medical care. Hospital admissions are assessed likewise, using the questions "Have you been admitted to a hospital in the past 12 months?" and "How many times have you been admitted to a hospital in the past 12 months?."

Socioeconomic background is given by the monthly household income per capita (monthly household earnings/number of family members). An income rank variable is used after organizing the individuals according to their household income per capita ranking. Individuals who did not declare their income were excluded from the sample.

For identification of inequality determinants, the explanatory variables of healthcare utilization were classified according to the type of contribution towards inequality: need and social determinants or non-need determinants.

In the group of need variables, we have demographic and morbidity variables. The non-need group includes the social dimension of utilization, taking into account variables that affect utilization directly through the relationship with the rank variable (calculated based on household income per capita) and with the need variables.

The demographic variables are represented by 12 sex-age dummies. Three questions are used in the PNAD to assess health status: a) In general, do you find your health status to be very good, good, fair, bad or very bad?; b) In the past two weeks, have you avoided doing any habitual activities for health reasons? and c) Questions about the 12 chronic diseases described in the questionnaires some physician or health professional is suspicious about.[5] These questions yielded four dummies for the perception of individual health status, a dummy for the presence of restrictions on habitual activities and, finally, a dummy for the presence of one of the 12 chronic diseases mentioned in the questionnaire.

The logarithm of household income per capita, years of schooling, the activity status in the labor market,[6] purchase of a health private insurance and place of residence were regarded as social determinants. Thus, four dummies were created for schooling, nine for activity status and one for the purchase of a health plan, in addition to five regional dummies.[7]

5. Empirical method and statistical inference

[5] The 12 chronic diseases mentioned in the questionnaires are: back or spinal cord diseases, arthritis or rheumatism, cancer, diabetes, bronchitis or asthma, hypertension, heart disease, chronic renal failure, depression, tuberculosis, tendinitis or tenosynovitis, and cirrhosis.

[6] The information about activity status, occupation and position refer to the week of reference.

[7] The following categories were used as reference: m10_17(male aged 10 to 17 years), very good health status, no schooling or less than one year of schooling, inactive and living in the northeastern region.

In the case of healthcare utilization models, the simplest approach would be to use a Poisson process for the probability of observing a given conditional event at a fixed time interval.

However, Poisson distribution assumes the equidispersion property, i.e., $E[y_i/X_i] = V[y_i/X_i] = \lambda_i$, a property that is commonly violated in healthcare utilization data, in which one often observes overdispersion of data, i.e., $E[y_i/X_i] < V[y_i/X_i]$. The check for the presence of overdispersion, we ran the test suggested by [17], on which it was not possible to reject the null hypothesis that data on doctor visits and hospital admissions are overdispersed.[8]

The hypothesis of equidispersion in the Poisson model was then relaxed by the introduction of an unobserved individual effect within the function to capture the overdispersion of data. We then obtained a negative binomial distribution that corresponds to the negative binomial model (Negbin II) described in [18][9]. In the presence of overdispersion, the negative binomial model yields consistent and efficient estimates, and is extensively adopted in the literature [18, 19-21].

The excess zeros in count data models, often regarded as a source of overdispersion, could be actually a strict implication of unobserved heterogeneity. This "intrinsic result of unobserved heterogeneity" occurs as a function of the type of healthcare and of the reasons for not utilizing it [22]. This is a shortcoming of the Poisson model (or negative binomial model), and a hurdle model should be used as alternative, where the assumption that excess zero and positive results share the same data generating process is relaxed.

As the intention was also to measure inequality in overall healthcare utilization, two forms of specification were adopted: hurdle models for healthcare utilization with a stepwise process and a negative binomial model for overall healthcare utilization.

In general statistical inference in studies that use the PNAD as a source of data assume that the data are obtained by a simple random sample with replacement, i.e., the observations are considered to be independent and identically distributed (iid). However, the PNAD has a complex sampling design and if this feature is overlooked, this could lead to biased variance estimates, also affecting the significance of parameters.

A complex sample as that of the PNAD involves stratification, clustering (multi-stage sampling) and different selection probability. A geographical stratification is carried out, according to which the country is split into 36 natural strata: (i) 18 states make up each an independent stratum and (ii) the remaining nine states (Pará, Ceará, Pernambuco, Bahia, Minas Gerais, Rio de Janeiro, São Paulo, Paraná and Rio Grande do Sul) make up two strata, one consisting of all municipalities of the metropolitan area and one with the other municipalities.

8 The results are not shown, but they are available from the authors upon request.

9 In Negbin II model, variance is a quadratic function of the mean $\lambda_i(1 + (1/\alpha)\lambda_i^2$, whereas in Negbin I, variance is proportional to the mean, $\lambda_i(1 + (1/\alpha)\lambda_i$.

In the nine strata formed by the metropolitan areas, the sampling is conducted in two stages and the primary sampling units (PSUs) consist of the census sectors. In the remaining 27 strata, the sampling is carried out in three stages: in the first one, the municipalities are the PSUs, which are classified into self-representative (probability 1 of belonging to the sample) and non-representative. The non-representative ones go through a stratification process in which the selection occurs with replacement and whose probability is proportional to the population size in the last census. In the second stage, census sectors are selected in each municipality by proportional probability and with replacement. Finally, in the third stage, household units are selected in each census sector with equal probability for investigation of housing and dwellers' characteristics.

Therefore, given the complex sampling design and the composition of contribution terms (given by the product of elasticities by the concentration indices of each determinant), a bootstrapping procedure is recommended for complex samples in order to obtain the estimates of the standard errors of the contribution terms [15].

A problem with the application of bootstrapping to the PNAD data is related to the strata with a single PSU of states that gave rise to two strata.[10] To solve this problem, the strata with single PSUs were identified and grouped into a new stratum within the same state. Finally, the estimation of standard errors included the creation of 100 weighting variables, applied to the estimation of the equation for weighted utilization by replicated weights and of the CI and of inequity (HIwv) which are also weighted by these weights.

6. Empirical results

6.1 Measurement of inequalities in healthcare utilization

Inequalities in the utilization of healthcare, doctor visits and hospital admissions were assessed by CIs and HIwv, shown in Table 1.

The CIs revealed that the utilization of doctor visits were strongly concentrated in higher income groups and that only Roraima and Santa Catarina had inequality indices that showed utilization by poorer individuals, but these indices were not significant. The degree of concentration in the utilization of doctor visits varied across geographical regions with small differences between the states of the same region. The states of the northeast region show largest income-related inequality in the utilization of doctor visits while those of the southern and southeastern regions show the smallest income-related inequality in the utilization of doctor visits

Few CIs was significant for hospital utilization in Brazil. CIs were only statistically significant in the states of Ceará, Paraíba, Rio Grande do Norte, Minas Gerais and Paraná.

[10] The estimation of standard errors included in the sampling design requires information on the stratum and on the PSU, in addition to the classification of municipalities into self-representative and non-representative. For further details about the sampling design of the PNAD, see [23].

The degree of inequality estimated by CIs may have been underestimated since poorer individuals often need more medical care and tend to use healthcare services more frequently than those who are better off. To capture only social inequalities in healthcare utilization, we calculated the horizontal inequality indices, which measure inequality between individuals with the same utilization needs.

Horizontal inequity indices in the utilization of doctor visits show that income-related inequality increases when individuals with the same utilization needs are taken into consideration; therefore, wealthier individuals utilize the services more than would be expected in relation to their needs. This result was observed in all regions. On the other hand, hospital admissions showed the opposite behavior, that is, poorer individuals utilize more hospital admissions than would be expected in relation to their needs.

Evidence of this type is found in the Brazilian literature when the consumption structure across groups is analyzed. Higher income groups use more outpatient services whereas lower income individuals use more hospital services [3, 8-10]. This suggests that wealthier individuals use preventive care more often while poorer people use intensive care more frequently.

Note that the high negative degrees of horizontal inequity for hospital care show large standard deviations; therefore, most proved not to be statistically significant. The inaccuracy of estimates of horizontal inequity for hospital care may result from the inability of need indicators to capture the necessity for hospital admission, often concentrated in less than 10% of the total sample.[11] Another explanation is that the determinants of hospital care utilization are more closely related to the characteristics of service providers, such as demographic characteristics of the health professional, professional experience, and form of payment of the service,[12] variables that are neglected by PNAD's supplemental issues.

Table 1 – Degrees of inequality in overall utilization of doctor visits and hospital admissions in Brazil and in Brazilian regions and states– 2008.

Brazil, Regions and states	Doctor visits		Hospital admissions	
	CI	HIwv	CI	HIwv
Brazil	**0.0738*** **	**0.0797*** **	**-0.0256*** **	**-0.00355**
	(0.00271)	**(0.00254)**	**(0.00726)**	**(0.00730)**
North	**0.0659*** **	**0.0587*** **	**-0.0399** **	**-0.0212**
	(0.00674)	**(0.00610)**	**(0.0200)**	**(0.0181)**
Rondônia	0.0508***	0.0706***	-0.0638	-0.0299
	(0.0160)	(0.0150)	(0.0411)	(0.0387)
Acre	0.0755***	0.0676***	0.00915	0.0538
	(0.0249)	(0.0230)	(0.0557)	(0.0529)
Amazonas	0.0549***	0.0486***	-0.0146	-0.0155

[11] According to PNAD data, only 7.2% of the sample stayed at least one day in hospital in 2008.
[12] Insured individuals have, on average, a smaller number of hospitalization days than those covered by SUS. This is usually due to health plan policies.

	(0.0153)	(0.0136)	(0.0659)	(0.0622)
Roraima	-0.000584	-0.00932	-0.0110	0.00373
	(0.0207)	(0.0162)	(0.0527)	(0.0515)
Pará	0.0883***	0.0738***	-0.0383	-0.0241
	(0.0114)	(0.0100)	(0.0236)	(0.0206)
Amapá	0.0790***	0.0943***	-0.0251	0.00105
	(0.0242)	(0.0204)	(0.166)	(0.162)
Tocantins	0.0209	0.0113	-0.0799*	-0.0654
	(0.0138)	(0.0137)	(0.0411)	(0.0415)
Northeast	**0.0933*** **	**0.0705*** **	**-0.0104**	**-0.0180**
	(0.00453)	**(0.00477)**	**(0.0117)**	**(0.0112)**
Maranhão	0.0265	0.0236	-0.0650*	-0.0366
	(0.0192)	(0.0209)	(0.0373)	(0.0370)
Piauí	0.0907***	0.0530***	0.0102	-0.0248
	(0.0110)	(0.0120)	(0.0256)	(0.0250)
Ceará	0.117***	0.0772***	0.0502***	0.0136
	(0.00799)	(0.00834)	(0.0193)	(0.0190)
Rio Gde do Norte	0.135***	0.120***	-0.0606*	-0.122***
	(0.0191)	(0.0184)	(0.0361)	(0.0366)
Paraíba	0.0845***	0.0425***	0.0700**	0.0407
	(0.0108)	(0.0119)	(0.0356)	(0.0340)
Pernambuco	0.0851***	0.0608***	-0.0458	-0.0332
	(0.00852)	(0.00798)	(0.0423)	(0.0407)
Alagoas	0.0631***	0.0456***	-0.0517	-0.0647
	(0.0172)	(0.0165)	(0.0594)	(0.0653)
Sergipe	0.0573***	0.0383***	-0.0159	-0.00921
	(0.0149)	(0.0130)	(0.0429)	(0.0385)
Bahia	0.0979***	0.0839***	-0.00992	-0.00942
	(0.00988)	(0.00999)	(0.0227)	(0.0209)

Brazil, Regions and States	Doctor visits		Hospital admissions	
	CI	HIwv	CI	HIwv
Southeast	**0.0440*** **	**0.0596*** **	**-0.0285** **	**-0.00211**
	(0.00411)	**(0.00354)**	**(0.0113)**	**(0.0108)**
Minas Gerais	0.0532***	0.0655***	-0.0424**	-0.0262
	(0.00733)	(0.00706)	(0.0173)	(0.0159)
Espírito Santo	0.0651***	0.0790***	-0.00142	0.0300
	(0.0173)	(0.0151)	(0.0503)	(0.0479)
Rio de Janeiro	0.0839***	0.0856***	0.0269	0.0370
	(0.00673)	(0.00626)	(0.0239)	(0.0231)
São Paulo	0.0120*	0.0320***	-0.0120	0.0197
	(0.00672)	(0.00604)	(0.0187)	(0.0176)
South	**0.0321*** **	**0.0585*** **	**-0.0409** **	**0.00377**
	(0.00557)	**(0.00571)**	**(0.0175)**	**(0.0177)**
Paraná	0.0270***	0.0625***	-0.0786***	-0.0254
	(0.00879)	(0.00878)	(0.0236)	(0.0238)
Santa Catarina	-0.000658	0.0252*	0.00877	0.0501**
	(0.0145)	(0.0147)	(0.0280)	(0.0248)
Rio Gde do Sul	0.0557***	0.0783***	-0.0132	0.0261
	(0.00933)	(0.00730)	(0.0288)	(0.0287)
Central West	**0.0628*** **	**0.0836*** **	**-0.0444*** **	**-0.00631**
	(0.00735)	**(0.00660)**	**(0.0151)**	**(0.0148)**
Mato Gr. do Sul	0.0278*	0.0383***	0.0100	0.0348
	(0.0154)	(0.0146)	(0.0226)	(0.0217)
Mato Grosso	0.0296**	0.0520***	-0.0440	0.0143
	(0.0144)	(0.0132)	(0.0327)	(0.0363)

Goiás	0.0434***	0.0633***	-0.0348	-0.00741
	(0.00999)	(0.00926)	(0.0223)	(0.0219)
Distrito Federal	0.148***	0.165***	-0.0401	-0.0130
	(0.0108)	(0.0100)	(0.0287)	(0.0274)

Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1
Note: To calculate the need-standardized use, we estimated a negative binomial model.

6.2 Determinants of inequality in healthcare utilization

The exploratory analysis of income-related concentration in healthcare utilization allowed identifying the pattern of income-related inequality in doctor visits and hospital admissions, but it did not allow determining the causes for these inequalities. To answer this question, we decomposed the CIs of utilization of doctor visits and hospital admissions.

The decomposition analysis of inequality in healthcare utilization was based on a negative binomial model for overall utilization and also on a hurdle model, in which utilization is seen as a two-stage process: initial contact and subsequent contacts. In this case, the utilization of doctor visits was estimated using a logit model for positive utilization and a truncated negative binomial model for the conditional utilization of doctor visits. Due to the lack of convergence in the interactions of the truncated negative binomial model for hospital admissions, we used a truncated Poisson model.

Utilization determinants are classified into need and social; the latter of which are accountable for inequities in healthcare utilization. The contribution of each determinant to inequality is obtained by the product of the impact on the use (elasticity) by the degree of inequality within income distribution (concentration index). Positive determinants contribute towards a pro-rich inequality (favoring utilization by the rich), whereas negative contributions favor pro-poor inequality (favoring utilization by the poor).

The concentration indices showed that the morbidity and rank variables are inversely related, suggesting that the worse the position in income distribution, the higher the utilization needs. The major exception was the presence of chronic disease.[13] One of the reasons for the positive association between these variables may lie in the better access to diagnosis among wealthier individuals.

As the need variables have a positive impact on utilization, except for the dummy for chronic disease, they contribute to reducing pro-rich inequalities and increasing pro-poor inequalities. On the other hand, the contributions of social determinants are more varied.

The sex-age dummies showed a more heterogeneous contribution but, in general, the contributions of male sex dummies are less favorable to utilization by poorer individuals than the female sex dummies.

[13] The results are available from the authors upon request.

Income contributed to the pro-rich distribution of overall utilization of doctor visits and to the pro-poor distribution of the overall utilization of hospital admissions. This result, however, does not necessarily mean better utilization of hospital care by poorer individuals. Yet, it could indicate that poorer individuals can only benefit from healthcare when they require intensive care.

Another interesting finding is that the contribution of income in subsequent contact is substantially smaller than in the initial contact, which suggests that income is rather a limiting factor for access than for the amount of healthcare provided.

An income contribution lower than the HIwv value indicates that other socioeconomic variables contribute to unfair inequality in healthcare utilization, which can be observed in the significant contributions of schooling, of activity status, of the purchase of a health plan and of the region of residence.

Health private insurance was the social determinant that most contributed to a favorable inequality among wealthier individuals. However, as the decision to acquire a health private insurance is influenced by the health status, it could also involve some aspect related to morbidity.

Healthcare utilization is also affected by regional income inequalities, given that poorer regions have a smaller supply of medical services, which restricts their use by those individuals living in those regions. Regional contribution depends on income distribution and on the supply of health services in relation to the region of reference.

Finally, the remaining contributions result from factors that were not included in the model, aggregated in a residual term, measured by the generalized CI of the error term, which gives the measure of utilization not explained by the need and non-need factors. A value close to zero means good fit of the model.

Table 2 – Contribution of healthcare utilization determinants to inequality, Brazil - 2008

Variables	Doctor visits			Hospital admissions		
		Negative Binomial Hurdle Model			Poisson Hurdle Model	
	Negative Binomial	Logit	Truncated Negbin	Negative Binomial	Logit	Truncated Poisson
m18_29	0.0000	-0.0001***	0.0000*	0.0004***	0.0005***	-0.0001
m30_44	0.0000*	0.0000***	0.0000***	0.0002***	0.0002***	0.0000
m45_59	0.0013***	-0.0004***	0.0011***	0.0045***	0.0053***	-0.0056
m60_69	0.0028***	0.0006***	0.0017***	0.0066***	0.0083***	-0.0005
m70	0.0004***	0.0003***	0.0002**	0.0012***	0.0011***	0.0003
f10_17	-0.0047***	-0.0020***	-0.0024***	-0.0041***	-0.0032***	-0.0019
f18_29	-0.0069***	-0.0020***	-0.0041***	-0.0126***	-0.0141***	0.0005
f30_44	-0.0032***	-0.0013***	-0.0016***	-0.0038***	-0.0045***	0.0004
f45_59	0.0078***	0.0035***	0.0039***	0.0057***	0.0068***	-0.0007
f60_69	0.0084***	0.0038***	0.0043***	0.0044***	0.0065***	-0.0017
f70	-0.0002	0.0000	-0.0001	0.0026***	0.0025***	0.0007
Good	-0.0010***	-0.0005***	-0.0006***	-0.0011***	-0.0011***	-0.0004
Fair	-0.0100***	-0.0035***	-0.0065***	-0.0117***	-0.0104***	-0.0042***
Bad	-0.0064***	-0.0012***	-0.0045***	-0.0091***	-0.0067***	-0.0028***

Very bad	-0.0015***	-0.0002***	-0.0012***	-0.0023***	-0.0016***	-0.0007***
Restriction	-0.0018***	-0.0010***	-0.0011***	-0.0039***	-0.0038***	-0.0007***
Chronic	0.0125***	0.0069***	0.0072***	0.0104***	0.0090***	0.0050***
Lincomepc	0.0237***	0.0202***	0.0082***	-0.0256***	-0.0288***	-0.0046
Elementary	-0.0016**	-0.0054***	0.0012*	0.0000	-0.0018	0.0010
High school	0.0024***	0.0032***	0.0002	-0.0010	-0.0011	0.0010
College	0.0062***	0.0078***	0.0014*	0.0009	0.0004	0.0021
Unemployed	0.0011***	0.0003***	0.0009***	0.0027***	0.0038***	-0.0003
Hired	-0.0028***	0.0021***	-0.0044***	-0.0100***	-0.0102***	-0.0064***
Public servant	-0.0007***	0.0012***	-0.0012***	-0.0019***	-0.0016***	-0.0014**
Household worker	0.0008***	0.0002***	0.0007***	0.0019***	0.0021***	0.0007***
Without work card	0.0008***	0.0002***	0.0006***	0.0007***	0.0008***	0.0003*
Self-employed	-0.0004***	-0.0002***	-0.0003***	-0.0005***	-0.0006***	-0.0002**
Employer	-0.0022***	-0.0004***	-0.0019***	-0.0014***	-0.0013***	-0.0013**
Other	0.0025***	0.0011***	0.0018***	0.0018***	0.0023***	0.0004
private insurance	0.0364***	0.0233***	0.0193***	0.0287***	0.0371***	-0.0031
North	0.0011***	0.0008***	0.0006**	-0.0022***	-0.0020***	-0.0010
Southeast	0.0052***	0.0012***	0.0043***	-0.0002	0.0010	-0.0004
South	0.0006	-0.0004	0.0008*	0.0025***	0.0033***	0.0007
Central west	-0.0001	-0.0001***	-0.0011	0.0015***	0.0016***	0.0005**
GC_{ε}	0.0035	-0.0039	-0.0079	-0.0109	-0.0174	0.0168
CI	0.0739***	0.0542***	0.0198***	-0.0257***	-0.0176***	-0.00776**
HIwv	0.0797***	0.0507***	0.0405***	-0.0034	-0.0056	-0.0097**
Observations	319,288	319,288	212,937	319,288	319,288	22,989

*** p<0.01, ** p<0.05 and * p<0.1

These contributions may vary in relation to contact decision and across regions, which was illustrated by the regional comparison of determinants in the initial contact (access) and in subsequent contacts (amount of contacts).

The need determinants (demographic and morbidity variables) contributed to more than half of the inequality in the probability of seeking medical care in Brazil. Therefore, the inequality in healthcare utilization in favor of richer individuals arises mostly from the larger demand for healthcare by this group.

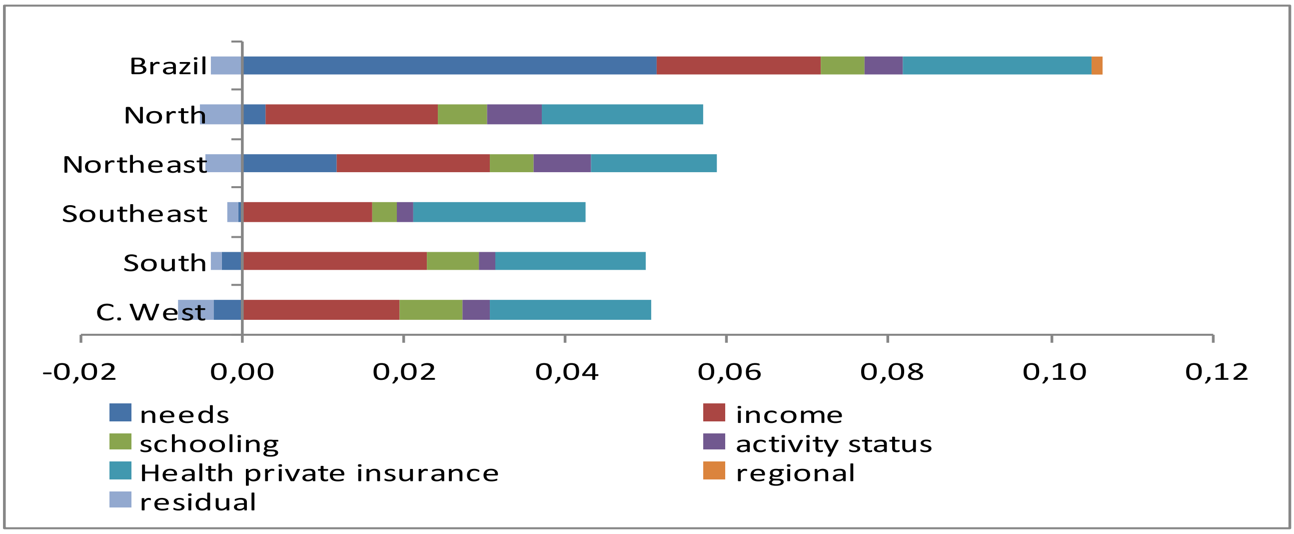
This controversial result can be understood when the need characteristics are examined in a disaggregated manner. The contribution of chronic diseases (0.0069) is, alongside health insurance (0.0233) and income (0.0202), the major determinant of pro-rich inequality in the probability of seeking medical care (Table 2), which reinforces the argument that larger healthcare utilization by higher income groups is associated with some type of medical follow-up for the treatment of chronic diseases.[14]

[14] As commented earlier, higher income groups have greater access to diagnosis, which also explains the weight of this determinant as explanatory variable for the utilization of doctor visits. However, this finding probably indicates only

When inequality is assessed regionally, the need characteristics contribute less to the inequality in contact, and income and health insurance are then the major determinants of inequality in the probability of seeking medical care (Graph 1).

greater access to diagnosis by wealthier individuals, rather than a lower incidence of chronic diseases among poorer individuals.

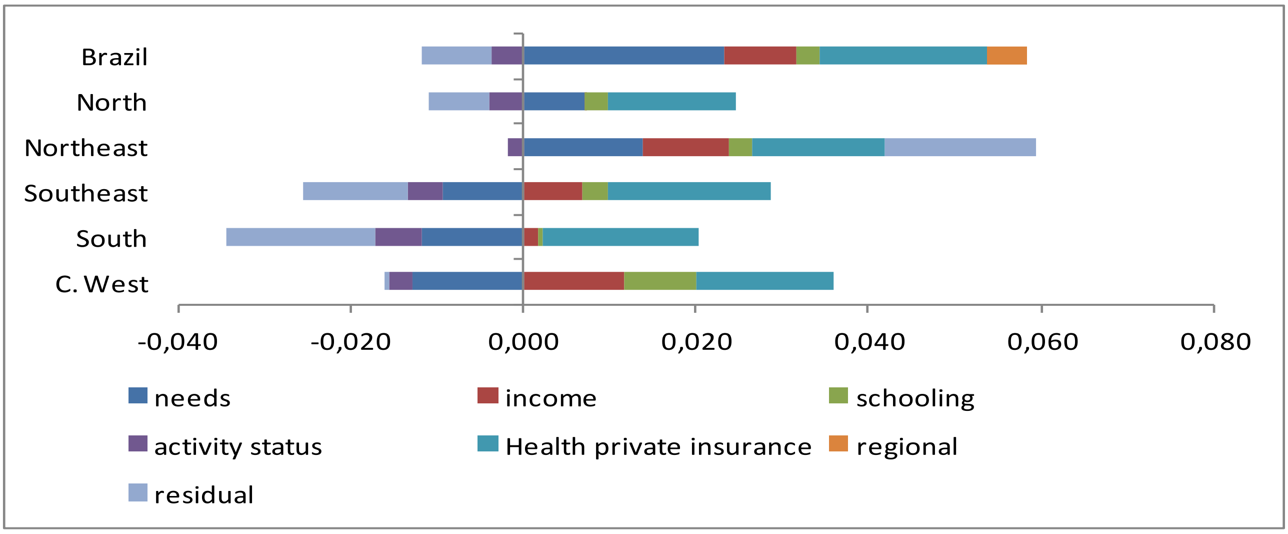
Graph 1 – Decomposition of inequality in the probability of seeking medical care, Brazil and Brazilian regions – 2008



Note.: Decomposition obtained from the marginal effect of the logit model

As to the inequality in the frequency of doctor visits, we observe the following: pro-poor contribution of activity status, probably due to the higher opportunity cost of active individuals compared to inactive ones to maintain the frequency in health treatment and income as an important source of pro-rich inequality, but with a smaller contribution than the purchase of a health insurance.

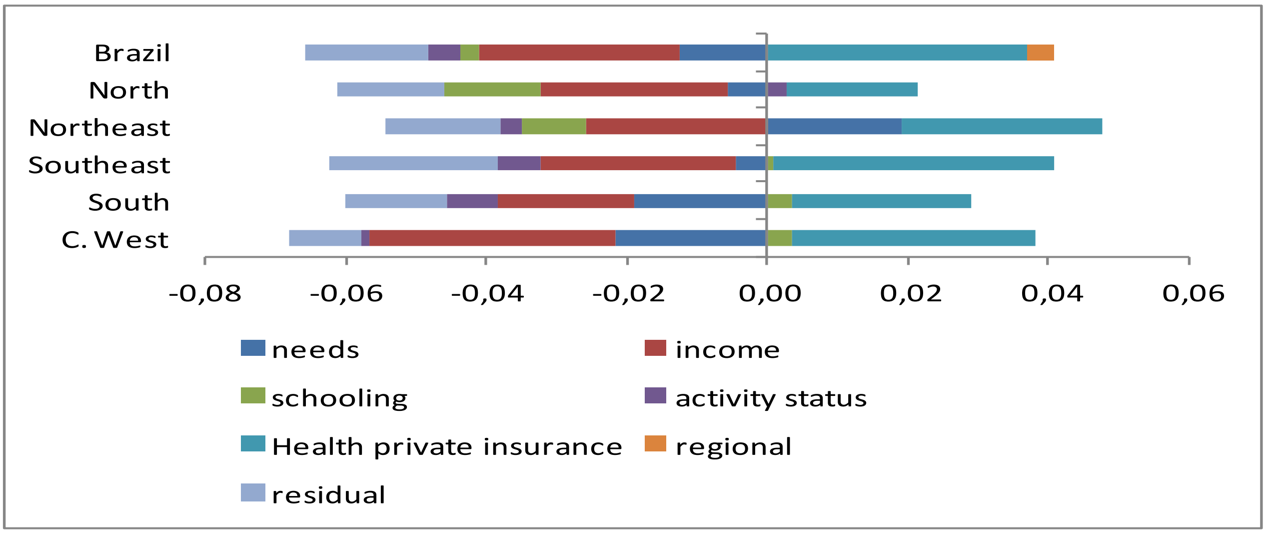
Graph 2 – Decomposition of inequality in the frequency of doctor visits, Brazil and Brazilian Regions – 2008



Note.: Decomposition obtained from the marginal effect of the truncated negative binomial model

When inequality was favorable to the poorer individuals concerning the probability of hospital admission, almost every determinant of inequality has a negative contribution, that is, they favor utilization by poorer individuals. The main exception was the contribution of health insurance, which helped reduce the pro-poor degree of inequality in the probability of hospital admission.

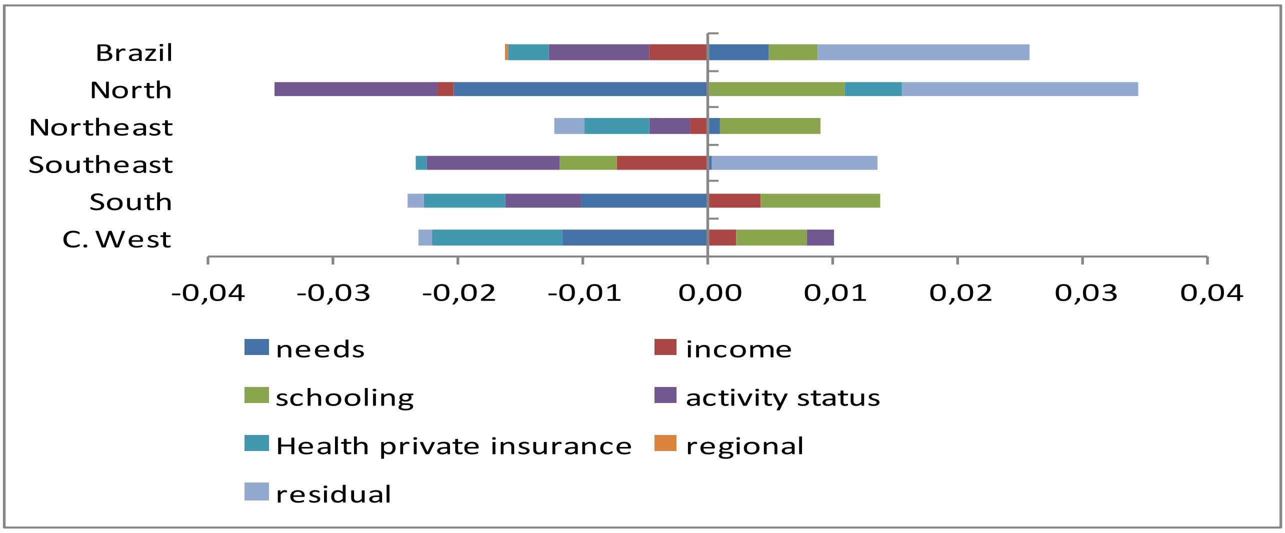
Graph 3 – Decomposition of inequality in the probability of hospital admission, Brazil and Brazilian regions – 2008



Note.: Decomposition obtained from the marginal effect of the logit model

The frequency of hospital admissions was also favorable to poorer individuals, and need and activity status were the factors that most contributed to pro-poor inequality.

Graph 4 – Decomposition of inequality in the frequency of hospital admissions, Brazil and Brazilian regions – 2008



Note.: Decomposition obtained from the marginal effect of the truncated Poisson model

It is worth pointing out that, except for inequality in the probability of doctor visits, the residual term made an important contribution to inequality in healthcare utilization. Part of this contribution can be ascribed to the characteristics related to the decision taken by health professionals, which could not be estimated, as they are not included in the database.

7. Conclusions

The Federal Constitution of 1988, aimed at guaranteeing that the whole population could have access to health, created the Unified Health System (SUS), the only public health system in the world that provides integral and universal access to healthcare. The literature shows that, despite universal coverage, inequalities in income-related healthcare utilization are persistent and strengthened by regional inequalities.

Therefore, in order to assess the equity in utilization of health services (doctor visits and hospital admissions), we calculated indicators of social inequality in healthcare and decomposed the causes of inequalities in healthcare utilization according to a regional perspective.

The hypothesis of horizontal equity in utilization was then tested by horizontal inequity indices, which measure unfair inequalities and those related to income. Given the regional difference in the supply of resources, the indices were constructed for each region and state so as to capture the regional characteristics of inequality in healthcare utilization.

The hypothesis of horizontal equity in the utilization of doctor visits was not confirmed in most of the Brazilian states, and a pattern of inequity was observed in the utilization of doctor visits in favor of those who are socioeconomically better off.

Although the high negative value of the horizontal inequity indices suggests a pattern of inequality in the utilization of hospital care in favor of poorer individuals, few Brazilian states yielded statistically significant indices, which leads to the conclusion that there is no inequity in the utilization of hospital care in most states. On the other hand, an inequality in the utilization of hospital care in favor of the poorer does not necessarily mean better utilization of hospital care by poorer individuals as this may also indicate that poorer individuals only have access to healthcare when they require intensive care. If that is the case, states with a high degree of inequity in the utilization of hospital care ought to increase their investment in primary care as a way to reduce hospital treatments in the case where they could be provided at basic health units.

The comparison of the regional degree of inequity shows that the magnitude of inequity in the utilization of doctor visits varies across regions, but much less across the states of a same region. The northeastern region concentrates the states with the largest horizontal inequities in the utilization of doctor visits whereas the southern and southeastern regions show the lowest degrees of inequity. Regional differences in inequality in utilization of doctor visits may be associated with the larger concentration of income in poorer regions and with the smaller supply of health services by SUS in less developed regions.

On the other hand, inequity in hospital care is more homogeneous across regions, but the central western region has the highest degree of income-related inequality. This more homogeneous regional distribution of inequity in hospital admission rates might result from better regional distribution of hospital beds.

However, the concern here is about inequity in income-related healthcare utilization as a function of individual characteristics that affect utilization. To understand how the determinants of utilization contribute towards inequality, the CIs were decomposed into social and health need determinants. Health need determinants, in general, contributed to favorable utilization by poorer individuals, given that these individuals need more healthcare. Social determinants had a more diversified contribution.

If, on the one hand, income favors the utilization of doctor visits by the rich, on the other hand, hospital care has a less pro-poor distribution. This means that the higher the income, the larger the utilization of doctor visits and the lower the rate of hospital admissions. This result is in line with the argument that poorer people use more intensive care than preventive care.

In addition to income, schooling, activity status, the purchase of a health private insurance and place of residence contributed socially to inequality in income-related healthcare utilization.

Schooling contributes to inequality in a similar way income does. Higher schooling levels contributed to increasing the pro-rich and pro-poor degree of inequality in the utilization of doctor visits and hospital care, respectively. The largest utilization of doctor visits by better educated individuals may be attributed to their greater awareness about the importance of healthcare, which leads to an increase in the demand for preventive health.

Nonetheless, activity status, in general, contributed to a more pro-poor distribution of healthcare utilization, which means that having a job may lead to a higher opportunity cost for individuals that are better off economically.

The contributions of purchase of a health private insurance and place of residence, however, are the ones that draw more attention from public policymakers as they are the main target of health policies. In this respect, contributions to the utilization of health insurance plans and of the place of residence by the rich in Brazil could be reduced, for instance, by a healthcare coverage focused on low-income people and by the higher supply of physical and human resources to areas where health services are scarce.

Conflict of Interest

The authors declare no conflict of interest.

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