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Multiple inequity in health care: An example from Brazil

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ABSTRACT

The paper develops and illustrates a new multivariate approach to analysing inequity in health care. We measure multiple inequity in health care relating to multiple equity-relevant variables – including income, gender, ethnicity, rurality, insurance status and others – and decompose the contribution of each variable to multiple inequity. Our approach encompasses the standard bivariate approach as a special case in which there is only one equity-relevant variable, such as income. We illustrate through an application to physician visits in Brazil, using data from the Health and Health Care Supplement of the Brazilian National Household Sample Survey, comprising 391,868 individuals in the year 2008. We find that health insurance coverage and urban location both contribute more to multiple inequity than income. We hope this approach will help researchers and analysts shed light on the comparative size and importance of the many different inequities in health care of interest to decision makers, rather than focus narrowly on income-related inequity.

1. Introduction

In the wake of the global universal health coverage movement, the issue of equity in health care is high on policy agendas in low, middle and high-income countries (Evans and Etienne, 2010; WHO, 2013). The number of publications in this area continues to increase and methods are developing rapidly, allowing more accurate measurement and better information for policy makers (Costa-Font and Cowell, 2017; Decancq et al., 2017; O. O'Donnell et al., 2008).

During the 1990s and 2000s, research on inequity in health and health care focused on "bivariate" measures of unfair inequality based on the relationship between two main variables of interest: a health variable and a single equity-relevant variable of concern to policy makers, most frequently income or socio-economic status (Yukiko Asada et al., 2014; Mackenbach and Kunst, 1997; Adam Wagstaff et al., 1991). Particularly influential was the work of the European Ecuity project team, who developed a powerful suite of bivariate measures based around the concentration curve – the natural extension of the univariate Lorenz curve to encompass the bivariate case – and disseminated these methods world-wide in training materials sponsored by the World Bank (O'Donnell et al., 2008). Several researchers subsequently refined this approach, resulting in a proliferation of bivariate indexes (Erreygers, 2006, 2009; A. Wagstaff, 2005, 2011; A. Wagstaff and Watanabe, 2003).

Lately, health researchers have started to examine *multivariate* inequality metrics, which allow simultaneously for multiple unfair sources of health inequality (Fleurbaey and Schokkaert, 2011; Norheim and Asada, 2009). Hitherto, however, this approach has almost exclusively been applied to unfair inequality in health outcomes rather than unfair inequality in the delivery of health services. The phrase *multivariate inequality measure* from the equity literature, which refers to the use of multiple equity-relevant predictor variables, is not to be confused with the phrase *multivariate regression* from the statistics and econometrics literature, which refers to regression analysis where there is more than one outcome variable. Furthermore, it should also be distinguished from research on *multidimensional inequality measures*, involving inequality in the distribution of multiple different goods – such as income, health, education and others (Atkinson and Bourguignon, 1982; Lugo, 2005). Research on multivariate inequality measures has drawn inspiration from the inequality of opportunity literature, which emphasises the distinction between "circumstances" for which the individual cannot be held responsible, and "effort" for which the individual can be held responsible (Fleurbaey and Schokkaert, 2011). For the purposes of this paper, an adapted version of this distinction is applied to the case of equity in health care, by distinguishing between "fair" variation in health care, such as variation related to individual needs and preferences, and "unfair" variation related to equity-relevant variables that should not be related to the use of health care. We define multiple inequity as inequality coming from multiple unfair sources that should not influence the use of health care.

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The main aim of this paper is to develop a new multivariate approach for measuring multiple inequity in health care. We use physician visits in Brazil as an illustrative example. Brazil is an interesting case study due to its large population (more than 210 million inhabitants in 2018), middle-income status and highly unequal distribution of income – with a Gini of 54.0 in 2008, the year we study in this paper, although income inequality has decreased slightly in recent years (2011 Gini = 52.9; 2015 Gini = 51.3) (Bank, 2018).

The paper contributes to knowledge in three ways. First, it contributes methodologically by providing the first application of the Fleurbaey and Schokkaert multivariate approach to measuring multiple unfair inequality in health care (Fleurbaey and Schokkaert, 2011). To our knowledge, although the multivariate approach has been applied to inequality in health outcomes (Jones et al., 2014), it has not previously been used to analyse inequality in health care delivery in any country. Second, this paper further develops the multivariate approach by proposing a health care advantage rank (HCA) that allows the multivariate approach to make use of the standard apparatus of bivariate concentration index type measures. The multivariate approach can be applied using a univariate inequality index such as the variance or the Gini. However, we propose a way of using bivariate indices, such as concentration and slope indices, to make the framework more user-friendly for analysts and policy makers in the health field who are more familiar with bivariate inequality indices. We present our results using a concentration index, which is widely used in the literature and decomposable; allowing findings about multiple inequity to be compared with findings about income-related inequality and compared between studies and settings. Third, the paper addresses a potential bias in previous studies of equity in health care in Brazil, due to inappropriate need adjustment using disease prevalence variables that appear systematically to under-report need in disadvantaged communities.

The methods developed in this paper may be used in other settings, at national, subnational or regional levels, to provide insightful information in any setting where equity in health care is considered a policy objective.

1.1. Theoretical background

The standard bivariate concentration index type approach to measuring horizontal inequity in health care assumes that a person's likelihood of receiving care should not be correlated with their position in a socioeconomic hierarchy. In simple terms, the utilisation of health care, arising from interaction between supply and demand, can be written using the following reduced form equation:

$$hc_i = hc(\mathrm{N}_i,\ SES_i,\ \mathrm{X}_i) \qquad [1]$$

That is, health care for person *i*, hc_i, is a function of need variables (N_i), which may include age, sex and health status variables, socioeconomic status (SES_i), and a vector of other non-need variables, X_i, such as education, ethnicity, region, employment, insurance status and so on. SES is a single social ranking variable and could be income, education, social class or any variable ordered from more to less advantaged. It is assumed that need is an acceptable source of variation in the use of care – indeed, a desirable source of variation to achieve vertical equity in the sense of distributing health care according to need. The other variables, X, are assumed to be neither fair nor unfair sources of variation. However, insofar as these variables may mediate or confound the relationships of interest between need, socioeconomic status and health care utilisation, steps are taken to purge the influence of these “neutral” variables from the analysis. The aim of the analysis is then to assess how far utilisation of health care is correlated with the single equity relevant variable – socioeconomic status – after purging the influence of confounding variables and adjusting for fair variation associated with need. The greater the degree of correlation after allowing for need, the greater the degree of horizontal inequity.

Ideally one would go further and use structural modelling of supply and demand to identify causal pathways, for example using instrumental variable approaches. However, given data limitations that is hard to do in practice and so almost all analyses in this area – including the present one, as well as studies based on the conventional bivariate approach – continue to rely on reduced form econometric modelling of associations rather than structural econometric modelling of causal pathways. Standard empirical measures of socioeconomic inequity in health care are thus best thought of as measures of inequality associated with socioeconomic status, after controlling for need, rather than measures of inequality caused by socioeconomic status.

Once we are concerned with multiple unfair inequity, that is, inequity associated with multiple equity-relevant variables, a different partitioning of variables is required. We can still see health care use as a reduced form function of three vectors: “fair” sources of variation that appropriately contribute to differences between people; “unfair” sources of variation in health care use; and “neutral” variables, which are neither fair nor unfair determinants of variation but whose influence may mediate or confound the relevant associations. Thus, we can consider a reduced form health care utilisation function of the form hc ($\mathrm{f_i}$, $\mathrm{u_i}$, $\mathrm{n_i}$), where $\mathrm{f_i}$ denotes variables that produce fair inequalities in health care, $\mathrm{u_i}$ corresponds to unfair sources of inequality, and $\mathrm{n_i}$ corresponds to neutral variables. Commonly, the socioeconomic inequality literature assumes that $\mathrm{f_i} = (N)$, $\mathrm{u_i} = SES$, and all other variables are neutral. This approach, however, has the disadvantage of focusing only on a single unfair dimension of inequality. It also disallows treatment preference, P, as a potential “fair” source of variation in health care. Thus, as Fleurbaey and Schokkaert (2011) have proposed, it may be more useful to consider $\mathrm{f_i} = (N, P)$ and place most other variables in the unfair vector, alongside socioeconomic status.

The formula for health care utilisation can then be written:

$$hc_i = hc(N_i,\ P_i,\ SES_i,\ Z_i,\ X_i) \qquad [2]$$

In this function N_i stands for health care need variables, P_i for treatment preference variables, SES_{i} for socioeconomic status, $\mathrm{Z_i}$ for other variables considered “unfair”, and $\mathrm{X_i}$ for neutral variables considered neither fair nor unfair. In theory, P_i variables could include a range of preferences regarding medical treatment, from behaviour over seeking care to type of medical care sought. For the purposes of the medical example in this paper, however, P_i variables only refer to preferences in terms of seeking medical care. Finally, the division of variables into Z and X vectors is a tricky matter of value judgement; as is the choice of reference values when adjusting for “fair” variation. In our Brazil example, both needs (N) and treatment preferences (P_i) were considered fair.

The multivariate framework also allows for the possibility of neutral variables. The analyst or policy maker may have a clear view that some variables are fair sources of variation in health care use, such as morbidity, and that others are unfair sources of such variation, such as income and education. However, neutral variables can potentially exist which are considered neither fair nor unfair but which could potentially confound the results. In the case of health, for example, age and sex are often considered to be neutral variables and their influence purged through standardisation. For the purposes of our illustrative example, however, we carefully considered each variable individually and took the view that all included variables were either fair or unfair. When considering all variables in our empirical application, we had to decide whether each variable was fair, unfair or neutral. Some variables landed themselves more easily into one of the three categories. In our case, age, sex and self-assessed health were clearly fair sources of variation in health care delivery, given they reflect need. At the other end of the spectrum are the variables educational achievement, ethnicity, region, employment status, an urban/rural dummy and health insurance coverage. These factors should not influence the amount of care a person receives. Finally, we included the seat belt variable as a proxy for preferences in healthcare seeking behaviour, and as such, this variable was placed in the fair vector. It was only the variable family type that could, potentially, be considered neutral. However, looking at the results from the standardising regressions, we could see that families with younger children were less likely to visit the doctor. We do not believe that having younger children should decrease the amount of care one receives, although we can hypothesise that families with young children have less time and more difficulties making and attending a medical appointment. Thus, we chose to place this variable in the unfair vector, which resulted in us having no neutral variables in our model.

A central issue is then how to move from the measurement of multiple inequality to unfair inequality only (Y. Asada, 2010; Yukiko Asada et al., 2015; Lefranc et al., 2009; Trannoy et al., 2010; Van Kippersluis et al., 2009). Two measures have been proposed to resolve this issue and measure unfair inequality only, namely i) direct unfairness and ii) the fairness gap (Fleurbaey and Schokkaert, 2009, 75). Direct unfairness eliminates the "fair" sources of inequality in health care (i.e. need and preference for health care) by setting them at reference values, that is, by eliminating any variation that exists in the fair sources of inequality, and predicting the outcome based on "unfair" determinants only. It thus provides a direct measure of horizontal inequity due to unfair determinants, after purging the influence of fair determinants (i.e. needs and preferences). In the case of inequality in health care, direct unfairness can be calculated as follows:

$$hci_{du} = hci_{predicted}(N_{ref},\ P_{ref},\ SES_i,\ Z_i,\ X_{ref}) \tag{3}$$

Here $hci_{\text{predicted}}$ is the predicted probability of receiving care, holding the vector N (of need variables) and P (treatment preferences) at reference levels, allowing measures of socio-economic status [SES] and other "unfair" variables [Z] (such as education, region, urban status etc.) to vary, after purging the influence of any "neutral" variables, X. For the case of health, for example, one could consider sex to be a neutral variable, if one believes that the health status of an individual should not depend on whether he or she is a man or a woman. For the case of health care, however, it can often be argued that sex is a need variable, and therefore, fair – to give a somewhat trite example, it seems legitimate for women to receive more maternal health care than men. Hence, in our analysis, there are no neutral variables, which allows equation (3) to be reduced to:

$$hci_{du} = hci_{predicted}(N_{ref},\ P_{ref},\ SES_i,\ Z_i) \tag{4}$$

Turning our attention to the fairness gap, this instead explicitly models the vertical equity relationship between health care utilisation and its "fair" determinants (i.e. needs and preferences), after purging the influence of "unfair" variables by setting them to reference values. The degree of unfair horizontal inequity is then the difference between the predicted "fair" level of utilisation and the actual observed level (Fleurbaey and Schokkaert, 2009). For evaluating absolute inequality the focus is on the absolute difference, and for evaluating relative inequality one can example the relative difference or ratio. In the case of absolute inequality the formula for the fairness gap for the evaluation of health care inequality is given by:

$$hci_{fg} = hci - hci_{predicted}(N_i,\ P_i,\ SES_{ref},\ Z_{ref}) \tag{5}$$

In this case, the prediction is done by setting the vectors of "unfair" determinants SES and Z at reference values, while the "fair" determinants N and P are allowed to vary.

The second term on the right hand side of the equation gives a normative prediction of the health care this individual ideally should receive. In the traditional health care equity literature, this is known "need-predicted" health care. The main conceptual difference here is that treatment preferences are considered to be fair determinants of health care utilisation, as well as capacity to benefit or need variables. Hence we shall refer to this as the "appropriate" or "fair-determinant-predicted" amount of health care, rather than the "needed" or "need-predicted" amount of health care. According to Fleurbaey and Schokkaert, the advantage (or disadvantage) of an individual *i* is given by the gap between the health care they actually receive and the ideal one. This is, hence, her individual measure of health care from which one may calculate *multiple inequity*.

Unlike the measure of direct unfairness, the fairness gap (ratio) has different specifications for absolute and relative inequality. Equation (5) presents the specification in absolute terms. For the relative case, in the reduced form, where no neutral variables exist, the fairness gap is a ratio and can be defined as:

$$hci_{fr} = hci / hci_{predicted}(N_i,\ P_i,\ SES_{ref},\ Z_{ref}) \tag{6}$$

In the case of a binary outcome, such as whether or not the individual has had a physician visit, the observed health care either assumes the value zero when the person did not go to the doctor, or the value one, when the person has paid a visit. By contrast, the predicted probability of health care based on all observed characteristics will be a continuous variable. In line with previous applications to measuring inequality for health (García-Gómez et al., 2015; Trannoy et al., 2010), we use this continuous predicted probability of observed health care, which we refer to as "latent" health care, rather than the binary observed binary measure. This is done for the sake of simplicity, but also because between the observed variable and the "appropriate" health care there is variation due to the regression residual, which is arguably a matter of stochastic "noise" or "luck" rather than unfair inequality. Nonetheless, the chosen treatment implies that we are implicitly considering the stochastic "noise" or "luck" to be fair and not to include it in the resulting measure of multiple unfair inequality. In other words, there may be factors that are not modelled and prevent people from using the health care services. These will appear in the "luck" term, but since we consider them to be randomly distributed and uncorrelated with the unfair vector of contributors to inequality, they are deemed fair and are not accounted for in the individual measure from which multiple unfair inequality can be derived.

2. Methods

2.1. Standardising models

We use two different standardising models to analyse unfair inequality. The first model hereafter referred to as the basic model, focuses on socioeconomic status only. It examines the relationship between physician visits in the past 12 months (as the dependent variable), equivalised household income (as our primary measure of socio-economic status) and age, sex and self-assessed health (traditionally considered as need factors). The basic model serves as a comparative exercise, for illustrating the traditional bivariate approach and comparing it with our multivariate approach.

The comprehensive model includes several other non-need variables in the "unfair" Z vector including educational achievement, ethnicity, region, employment status, an urban/rural dummy, family type and health insurance coverage. We were initially unsure whether to consider the variable family type as fair, unfair or neutral. However, our standardising regressions showed that families with younger children were less likely to visit the doctor. We interpreted this as a sign of barriers to accessing services among such families, rather than a sign that having younger children decreases the need for physician visits. Thus we chose to place this variable in the unfair vector.

To illustrate how differences in preferences can be handled, we also included a further variable in the fair vector indicating whether the person uses a seat belt, as a proxy for healthcare seeking preferences. This latter variable was chosen as a proxy for preferences for health care seeking on the grounds that preferences for investing in health protection in the form of wearing a seatbelt may be correlated with one's preferences for investing in health more generally by seeking health care. Some theorists have proposed that attitudes to risk may explain health care seeking behaviour (Dardanoni and Wagstaff, 1987; Hersch and Pickton, 1995). In our context, a higher degree of risk aversion may be manifested in a higher likelihood of wearing a seatbelt to prevent possible injury following an accident. We therefore assume that people who are more likely to choose to wear a seat belt are also more likely to choose to seek health care, and that these are both rational individual choices.

Our partitioning of variables into "fair" and "unfair" vectors was based on a particular set of value judgements. To allow for different value judgements, we conducted a decomposition analysis that provides information about the contribution of each fair and unfair variable to multiple inequity. An alternative approach would be to conduct a series of sensitivity analyses by making different choices about which variables to place in the fair and unfair vector.

2.2. Modified concentration index

In the literature so far, applications of the multivariate approach to health outcomes have used the variance as the primary univariate measure of inequality, on the grounds that this is a simple and additively decomposable univariate measure (Jones et al., 2014). However, the variance is a mean-sensitive absolute measure of inequality (Atkinson, 1970) and is not commonly used in the health literature. We propose instead using a bivariate-type approach that the health policy community are more familiar with and may find easier to understand and use. Bivariate measures are by far the most common way of measuring inequality in health and health care in the health economic and epidemiological literature. A bivariate approach thus facilitates comparison between different studies and helps analysts, decision makers and stakeholders understand the meaning of the measure. We focus on one class of (relative) bivariate measure for our detailed analyses - the concentration index (and the Erreygers modification thereof) – though we recognise that other bivariate measures may be useful in different contexts, including absolute measures such as the slope index of inequality. We use the concentration index, to illustrate the methods because: i) it can be compared in both magnitude and decomposition with the results of concentration-index approaches that are popular in this area; ii) there is vast literature on the concentration index and its extensions, so this index is familiar to the health policy community; and iii) as a mean independent measure, the concentration index allows comparisons between inequality in different forms of health care with different mean levels.

Our proposed method for measuring inequality thus makes use of the traditional bivariate framework, while incorporating the multivariate measures of *direct unfairness* (hci_{du}) and the *fairness gap* (hci_{fr}). As the concentration index is a relative measure of inequality, both direct unfairness and the fairness gap must be defined in relative terms – so henceforth we refer to the latter as a fairness ratio rather than a fairness gap. The correct specification of both measures follows equations (4) and (7), respectively.

The conventional bivariate approach ranks individuals by a single equity-relevant variable: socioeconomic advantage. Our alternative approach ranks individuals by health care advantage relating to multiple equity-relevant variables.

Effectively, this can be done by replacing socioeconomic position on the x-axis with a ranking created using one of the multivariate measures i.e. either direct unfairness (hci_{du}) or the fairness ratio (hci_{fr}). This ranks people by how likely they are to receive appropriate care due to unfair advantages, with people towards the right having greater "unfair" access to health care than people towards the left. In short, it ranks individuals in terms of their degree of unfair (dis)advantage in accessing health care. We can therefore think of it as "unfair health care advantage rank", or HCA rank for short. The lowest ranked individual is the one that is least likely to receive appropriate care. In contrast, the highest ranked person has an unfair advantage in terms of likelihood of receiving appropriate care given their need and treatment preferences. We can then use the standard concentration index apparatus and the usual standardisation procedures, using the HCA rank as the ranking variable instead of socioeconomic status.

In this paper, the calculation of summary measures of inequality was based on individual measures of direct unfairness, although one could have created an HCA Rank based on individual measures of the fairness ratio. The choice to use direct unfairness was simply computational ease, as the same specification can be used for the relative and absolute cases. In theory, however, results using the two approaches can differ if the model is non-linear (as in our example) and if there are interaction terms (which there are not in our model).

Furthermore, according to Hosseinpoor et al. (2006) and Yiengprugsawan et al. (2010) in binary health variables, such as physician visits, the choice of reference values for the estimation of the standardising regression matters, once the proportion of people in each reference group varies, and this influences the estimated value of the predictions (Yiengprugsawan et al., 2010). In fact, given that the concentration index is a ratio and that the setting of different reference groups alters the mean of the predicted standardising regression, one can expect the final inequality measure to change for different reference category groups.

The standardising regressions were used both for calculations in the bivariate and multivariate approaches. Particularly for the multivariate approach, as unfair variables are not neutral, we had to choose a reference group in terms of health care. In all categories, with the exception of income, we have chosen the best group in terms of health care use. Therefore, for education, our reference group was higher education, for region, the South-East, in terms of ethnicity, we chose white individuals, who lived in urban areas, were covered by health insurance and always wear a seatbelt. There are two reasons for this choice: i) the number of individuals who do not ride in the front seat is fairly small, and this may not reflect their risk perception, but other cultural characteristics; and ii) one who chooses to always wear a seatbelt could be perceived as someone who is very averse of the risk of injury by accident. Finally, the choice about employment was a bit trickier. One could argue that individuals who are employed are better off, as they have means of income and social insertion. However, as unemployed people appear to use health care in the form of physician visits more often, we decided to set them as a reference group. The argument here is that ideally, people would be able to attend the doctor whenever they felt the need, and working should not be an obstacle in any way. To guarantee comparability between the multivariate and bivariate approaches, we chose mean income as reference.

As one of the main purposes of the proposed approach is for it to be directly comparable to income-related inequality measures, we have chosen to estimate three distinct measures of inequality: (1) the directly standardised concentration index (CI), (2) the horizontal inequality index (HI), which is equivalent to the indirectly standardised concentration index and (3) the Erreygers modified concentration index, which modifies the directly standardised concentration index to allow for the bounded nature of a health care variable in a way that preserves mirror, monotonicity and level of independence properties (Erreygers, 2009).

The directly standardised concentration index of health care based on direct unfairness is given by:

$$CI_{direct} = \frac{2\,Cov(hci_{direct},\ F(hci_{du}))}{\mu hc} \qquad [7]$$

where hci_{direct} is the directly standardised individual measure of health care, $F(hci_{du})$ is the cumulative distribution function of direct unfairness and μhc is the mean level of health care across the population. We explore the relationship between our proposed concentration index based on health care advantage rank approach and the Gini Index approach as proposed by Fleubaey and Schokkaert (2011) in Appendix 1 [INSERT LINK TO ONLINE APPENDIX 1].

In turn, the Horizontal Inequity Index (HI) is computed by subtracting the observed measure of health care on latent scale from the fair-determinant-predicted one – thus providing an index of unfair inequality in health care received, allowing for the "appropriate" level of health care given the individuals' needs and treatment preferences. This is the equivalent of indirect standardisation. Mathematically, the Horizontal Inequity Index is defined as:

$$HI = CI - CI_{fair-determinant-predict} \quad [8]$$

Which in turn can be expressed in terms of covariances as follows:

$$HI = \frac{2Cov(hci,\ F(hci_{du}))}{\mu hc} - \frac{2Cov(hci_{fairdeterminantpredict},\ F(hci_{du}))}{\mu hc_{fairdeterminantpredict}} \quad [9]$$

Finally, the fair-determinant-predicted function that defines $\underline{hci}_{\text{fair-determinant-predict}}$ is:

$$hci_{fair-determinant-predict} = hci_{predicted}(N_i,\ P_i,\ SES_{ref},\ Z_{ref}) \quad [10]$$

The prediction formulated in equation (10) holds socioeconomic status and other unfair variables at reference levels, while allowing for need and treatment preference variables to vary.

Finally, the Erreygers modified concentration index is based on a simple transformation of the concentration index, defined as:

$$Erreygers\ CI = 4 * \mu hc * CI_{direct} \quad [11]$$

Our choice of reporting is justified by two reasons. First, we want to illustrate that the modification we are proposing is not a modification of the concentration index *per se*, but of the type of inequality being measured, thus, all indices can be applied. Second, each of the indices implies a different normative perception. The standard concentration index, for example, is a relative measure, so its bounds decrease as the mean of the outcome variable increases. Erreygers' modification, on the other hand, is sensitive to the mean and no longer can be considered a relative index (Wagstaff, 2009). We appreciate that different researchers and policy makers may have different views on inequality, therefore, we leave it for the reader to choose the most appropriate one.

Regarding the interpretation of the measures proposed, as in the income-related inequality literature, one could interpret the horizontal inequity index as an indication of the magnitude of pro-advantaged inequity in health care. In this case, however, "advantaged" does not mean rich or poor, but relates to the individual's position in the Health Care Advantage Rank, which depends on multiple sources of unfair advantage to health care. A negative index of multiple inequity in health care indicating "pro-disadvantaged" inequity can also potentially arise, if the list of "unfair" determinants of health care is pre-specified without reference to the regression results. However, if the list of "unfair" determinants is chosen endogenously by deliberately selecting only factors that predict lower observed health care, then "pro-disadvantaged" inequity cannot arise.

The concentration index also allows us to decompose the contribution of each "fair" and "unfair" source of inequity to multiple inequality (O'Donnell et al., 2008, 159). This can also be understood as a form of sensitivity analysis, with regards to different normative positions around unfair inequality. Our decomposition calculates the marginal impact of neutralising the variable of interest, i.e. the factors in the decomposition, on the concentration index (O'Donnell et al., 2013; Yiengprugsawan et al., 2010). This is referred to as the "Shapley value" decomposition, because it turns out to be formally equivalent to the Shapley value solution in cooperative game theory (Shorrocks, 2013). Considering that the proposed measure of multiple unfair inequality falls into the concentration index category, the interpretation of the decomposition is analogous to that performed in income-related inequity – except that we are decomposing the contribution of different variables to multiple inequity rather than just their contribution to income-related inequity.

2.3. Data

The data used in this paper comes from a cross-sectional household survey carried out by the Brazilian Institute of Geography and Statistics in 2008. The health supplement of the Household Sample Survey (*Pesquisa Nacional por Amostra de Domicílios* or PNAD) was carried out in 1998, 2003 and 2008 before being discontinued. To define its sample, PNAD made use of a complex three-stage probabilistic distribution, the results being representative of the population at a national level, regional level and federal states levels (IBGE, 2008). This paper uses data only for 2008, composed of over 391,868 individuals, from which a random sample of 10% is used for analysis. By using the national survey, we have used secondary survey data for which informed consent is obtained by IBGE, including the provision for data sharing and future use.

Most of the variables, including income, ethnicity and sex, rely on self-report, though region and urban-rural status were directly observed by the survey investigators. The variable income refers to the log of household income equivalised using the square root of household size. Self-assessed health is reported in five categories ranging from very bad to very good. We chose to include education in terms of highest qualification achieved, rather than years of schooling, since in Brazil it is not uncommon for individuals to attend school for a number of years and not achieve the corresponding educational level. We also included dummy variables for private health insurance coverage and employment. These last two variables are relevant in the context of the Brazilian health care system since, as well as a tax-based public health care system, Brazil also has a substantial private health expenditure, corresponding to circa 46% of the total expenditure in health care (Bank, 2014). In turn, private health care expenditure is 55% out-of-pocket spending and 45% financed by private health insurance. Thus, private health insurance accounts for roughly 20% of all health care expenditures. In Brazil, private health insurance can be bought by individuals or families, but most commonly is offered as an employment-based benefit in large companies (about 3 in every 4 individuals covered by private health insurance have employment-based insurance). Notwithstanding, for circa 75% of the population, the only health care available is the national tax-based public system. Appendix 2 [INSERT LINK TO ONLINE APPENDIX 2] shows some relevant descriptive statistics.

Finally, we have explicitly chosen not to include chronic conditions as a need variable, given that graphs of chronic condition by income groups (Supplementary materials – Appendix 3 [INSERT LINK TO ONLINE APPENDIX 3]) show substantially higher rates of self-reported chronic illnesses in higher socioeconomic groups. This suggests that chronic conditions are substantially under-diagnosed in socially disadvantaged individuals in Brazil, perhaps due to lack of access to primary care. Previous work using this same survey data has treated self-reported chronic conditions as standardising variables indicating need for care, but if under-diagnosis of more deprived groups exists this may under-estimate the degree of health care inequality. So we use age, sex and self-assessed health alone as the main need standardising variables. We have carried out the analysis including chronic conditions as a robustness check. As expected, this reduces the measured extent of health care inequality, and the results can be found in Appendix 4 [INSERT LINK TO ONLINE APPENDIX 4].

3. Results

Table 1 presents the marginal effects and standard errors of the two standardising models based on logit regression.

The coefficients all have plausible signs and, as expected, the size of the income coefficient decreases as more social variables are included. In sensitivity analysis, we explored the use of interaction terms, but found that interactions were generally small or insignificant and so for simplicity have left them out of the final models.

3.1. Income-related inequality versus unfair multiple inequality

Table 2 displays our proposed measure of unfair multiple inequity

Table 1
Standardising regressions – marginal effects and standard errors.

	Basic		Comprehensive	
	mg eff	se	mg eff	se
ln(income)	0.067	0.003	0.016	0.004
Male				
Female	0.180	0.004	0.173	0.004
Age group (base: younger than 15 years of age)				
15–29	−0.086	0.009	−0.029	0.007
30–44	−0.020	0.009	0.011	0.007
45–60	0.005	0.009	0.025	0.006
60 +	0.046	0.012	0.073	0.007
Self-Assessed Health (base: Very Good Health)				
Good	0.062	0.006	0.077	0.007
Regular	0.215	0.004	0.240	0.004
Bad	0.322	0.006	0.348	0.006
Very Bad	0.310	0.010	0.352	0.010
Educational Achievement (base: no education)				
Primary			0.009	0.009
Secondary			0.041	0.005
Higher			0.062	0.010
Undetermined			0.099	0.011
Region (base: North)				
North East			0.022	0.009
South East			0.054	0.005
South			0.026	0.005
Centre West			0.022	0.008
Ethnicity (base: white)				
Native			−0.041	0.063
Black			−0.006	0.004
Asian			0.003	0.004
Mixed			−0.034	0.092
Urban (Craig et al., 2003)				
Rural			−0.039	0.003
Employment Status (base: occupied)				
Unoccupied			0.012	0.004
Family Type (base: no children)				
children under 14			−0.007	0.009
children 14+			0.084	0.015
Health Insurance (base: No)				
Yes			0.135	0.006
Seatbelt Preference (base: always)				
Doesn't ride in front seat			0.001	0.009
Often			−0.038	0.004
Sometimes			−0.052	0.014
Rarely			−0.061	0.011
Never			−0.056	0.012
Adjusted R-squared		0.0849		0.1153
Number of observations		34624		28067

Table 2
Unfair Multiple inequity *vs* Income-related Inequity.
Source: National Household Sample Survey (PNAD), Health Supplement, 2008.

	Basic		Comprehensive	
	Income-related	*Unfair Multiple*	*Income-related*	*Unfair Multiple*
CI	0.0541	0.0543	0.0478	0.0702
HI	0.0504	0.0539	0.0581	0.0852
Erreygers CI	0.1424	0.1425	0.1284	0.1884

Notes: 1) HI = $CI_{observed} - CI_{predicted}$.
2) $CI_{observed}$ measured on a latent scale.
3) Erreygers CI = 4*μ*CI.

alongside traditional bivariate measures of income-related inequity for each case – including Concentration Indices (CI) and Horizontal Inequity Indices (HI), and the Erreygers corrected Concentration Index (Erreygers CI). The HI is given by the difference between the Concentration Index for observed health care and the Concentration Index for "appropriate" or "fair-determinant-predicted" health care in the case of unfair multiple inequality.

Table 3
Decomposition of the Unfair Multiple Inequality using CI.
Source: National Household Sample Survey (PNAD), Health Supplement, 2008.

Basic		
	Contribution	Percentage Contribution
Income	0.02907	53.56%
Residual	0.02521	46.44%
Total	0.05428	100.00%
Comprehensive		
	Contribution	Percentage Contribution
Ethnicity	0.00014	0.20%
Employment Status	0.00027	0.38%
Region	0.00101	1.43%
Family Type	0.00175	2.49%
Education	0.00426	6.07%
Income	0.00626	8.91%
Urban Status	0.00708	10.08%
Health Insurance	0.04354	61.99%
Residual	0.00593	8.44%
Total	0.07024	100.00%

As expected, the basic model yields virtually the same results (to the third decimal place) in the traditional income-related bivariate analysis and our proposed HCA rank approach. For the comprehensive model, which considers eight sources of unfair inequality (income, educational achievement, region, ethnicity, employment status, an urban/rural status, family type, health insurance coverage) and one extra source of fair inequality (behaviour towards health care), the measure of multiple unfair inequality is larger than that of income-related inequality, focusing on just the one source of unfair inequality.

Table 3 presents the decomposition of multiple unfair inequality using the standard concentration index (CI), which helps understand how far income and all the other social variables contribute to unfair multiple health care inequity. To simplify the reporting of the decomposition analysis, we re-ran the standardising models treating age and categorical covariates (SAH, education, region, ethnicity, family type and seatbelt preference) as continuous or ordinal variables as appropriate, rather than large sets of dummy variables.

Briefly, the table shows that the relative contribution of income drops sharply as we move from the basic to the comprehensive model. That is understandable, as income is the only unfair source of inequality in the first model, while other sources are included in the other ones. In the comprehensive model, by contrast, the largest contribution to unfair inequality is made by health insurance coverage. That implies that individuals with insurance are considerably more likely to visit a doctor than their uncovered counterparts, irrespective of their income or education status. Also in the comprehensive model, urban status appears to be more important than income. Thus, living in urban regions can compensate being relatively poorer. The reasoning behind this fact is related to difficulty in access of health care providers in rural areas, but may be also perceived as an indication of better supply of services in urban settings.

4. Discussion

The measurement of equity in health care remains dominated by a bivariate approach that focuses only on one equity-relevant variable at a time – typically income or socioeconomic status. This paper generalises the standard approach by allowing simultaneously for multiple equity-relevant variables, drawing on theoretical work by Fleurbaey and Schokkaert (2009, 2011) and others and extending it by showing how familiar bivariate indices can still be applied in the case of multivariate analysis of multiple unfair inequality in health and health care.

Like Fleurbaey and Schokkaert, we propose using standardising regressions to compute artificial distributions of unfair health care inequality, known as *direct unfairness* and the *fairness gap*. Unlike Fleurbaey and Schokkaert, however, we propose using bivariate rather than univariate indices to assess inequality in this artificial distribution, on the grounds that bivariate indices are more familiar in the health literature. We propose ranking individuals according to their position in the artificial distribution to create an index of unfair Health Care Advantage (HCA), and subsequently using this ranking to apply the standard apparatus of the bivariate approach: the concentration index and decomposition thereof. We illustrate the approach through an application to the utilisation of physician services in Brazil in 2008. We find that multiple inequity is much larger than income-related inequity and that having private health insurance and residing in an urban area contribute more to multiple inequity than income.

To illustrate how our method compares with the conventional bivariate approach, we also analysed a basic model where the only equity-relevant variable is income. Our analysis illustrated that, for the basic model, the traditional income-related bivariate analysis and our proposed HCA rank approach produced the same results. That is because the only illegitimate source of inequality in the basic model is income (SES) and the legitimate ones are sex, age and self-assessed health – i.e. the same assumptions as made in the income-related inequality framework. In the comprehensive model, however, the unfair multiple indices are substantially larger than their income-related counterparts.

The current study has a number of limitations. First and foremost, like all the rest of the empirical literature on equity in health care, our study does not rely upon structural modelling and cannot draw inferences about causality. Our assessment of multiple inequity, and the relative size and importance of different components of multiple inequality, is based on analysis of associations rather than analysis of causal pathways. Even though we cannot disentangle the structure of causal pathways from our reduced form models, however, it does not seem plausible that the strong associations found between physician visits and the other equity-relevant non-income variables are merely picking up measurement error in the income variable. Furthermore, even if the associations found with other equity-relevant variables were entirely due to measurement error in the income variable, policy makers would still be interested in our findings, as they help identify unfair inequalities that are not picked up by looking at associations with observed income only.

Second, our three need variables (age, sex and self-assessed health) are imperfect and incomplete measures of need for physician visits. We deliberately chose not to use available data on chronic conditions, however, due to evidence that these are seriously under-reported by individuals with poor access to health services including diagnostic services. How far this is simply a reporting bias or an indication of under diagnosis remains an open question. Third, self-assessed health may suffer from reporting bias, although any such the bias is not so serious as to reverse the sign of the adjustment; furthermore studies have shown this to be both a good indicator of health as well as of health care us (DeSalvo et al., 2005; Idler and Benyamini, 1997). Lastly, there are other measurement errors and limitations in the survey data used, as is often the case in developing countries.

Income-related inequality in health care in Brazil had been previously measured (Almeida et al., 2013; Macinko and Lima-Costa, 2012). Both studies found concentration indices smaller in magnitude: 0.033 and 0.0429 respectively, while we have found income-related inequality to have a CI of, atat least, 0.0478 and multiple inequity to have a CI of 0.0702. We believe this difference in income-related inequality concentration indices derives from their adjustment for chronic conditions. Such conditions seem to be incorrectly represented in the survey. Whether this is simply a reporting bias or indeed an indication of under diagnosis remains an open question.

Finally, our analysis of multiple inequity produced policy relevant information about the relative importance of different equity-relevant variables. We found that private health insurance coverage and urban status contribute more to unfair inequality than income and other equity-relevant variables. As far as private health insurance is concerned, the government could choose to incentivise individuals and companies to join in private insurance schemes. This would potentially increase access to health care for those joining, but might increase multiple unfair inequity if those who cannot afford or participate in such schemes become even worse off in terms of access to care. Regarding the importance of urban status, the government could potentially reduce the measure of multiple unfair inequity by investing in allocating health care resources, particularly, medical doctors, to the Brazilian countryside. Allocating resources to the countryside has been, to some extent, a policy priority for the last 20 years, with the dissemination of the Family Health Programme (Programa Saude da Familia), although its direct effect on reducing inequalities remains unclear (Brasil, 2013a, b; Mendes and Marques, 2014; Vasconcellos, 2013).

We hope that analysts and decision makers will find the multiple inequity approach useful as a way of comparing the relative importance of different kinds of unfair inequality in health care delivery, and that researchers will improve the methods over time as they start to be applied in practice.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2019.02.034.

References

Almeida, G., Sarti, F.M., Ferreira, F.F., Diaz, M.D., Campino, A.C., 2013. Analysis of the evolution and determinants of income-related inequalities in the Brazilian health system, 1998 - 2008. Rev. Panam. Salud Públic 33 (90–97) 94 p preceding 90.
Asada, Y., 2010. On the choice of absolute or relative inequality measures. Milbank Q. 88, 616–622 discussion 623-617.
Asada, Y., Hurley, J., Norheim, O.F., Johri, M., 2014. A three-stage approach to measuring health inequalities and inequities. Int. J. Equity Health 13, 98.
Asada, Y., Hurley, J., Norheim, O., Johri, M., 2015. Unexplained health inequality - is it unfair? Int. J. Equity Health 14, 11.
Atkinson, A.B., 1970. On the measurement of inequality. J. Econ. Theor. 2, 244–263.
Atkinson, A.B., Bourguignon, F., 1982. The comparison of multidimensional distribution of economic status. Rev. Econ. Stud. 183–201.
Bank, W., 2014. World Bank Database. Development Research Group.
Bank, W., 2018. World Bank Database. Development Research Group.
Brasil, 2013a. Financiamento Público em Saúde. In: Saúde, M.d. (Ed.), Brasília, DF.
Brasil, 2013b. Sala de Apoio a Gestão. In: Brasília, D.F. (Ed.), Ministério da Saúde.
Costa-Font, J., Cowell, F., 2017. The Measurement of Health Inequalities: Does Status Matter? CESifo Working Paper Series No. 6117.
Craig, D., Nixon, J., Armstrong, N., Glanville, J., Kleijnen, J., Drummond, M., et al., 2003. New BMJ policy on economic evaluations. Response of NHS economic evaluation database research team. BMJ 326, 445 author reply 445.
Dardanoni, V., Wagstaff, A., 1987. Uncertainty, inequalities in health and the demand for health. J. Health Econ. 6, 283–290.

Decancq, K., Fleurbaey, M., Schokkaert, E., 2017. Wellbeing inequality and preference heterogeneity. Economica 84, 210–238.
DeSalvo, K.B., Fan, V.S., McDonell, M.B., Fihn, S.D., 2005. Predicting mortality and healthcare utilization with a single question. Health Serv. Res. 40, 1234–1246.
Erreygers, G., 2006. Correcting the Concentration Index. University of Antwerp.
Erreygers, G., 2009. Correcting the concentration index. J. Health Econ. 28, 504–515.
Evans, D.B., Etienne, C., 2010. Health systems financing and the path to universal coverage. Bull. World Health Organ. 88, 402.
Fleurbaey, M., Schokkaert, E., 2009. Unfair inequalities in health and health care. J. Health Econ. 28, 73–90.
Fleurbaey, M., Schokkaert, E., 2011. Equity in health and health care. In: Pauly, M.V.M., Thomas, G., Barros, Pedro P. (Eds.), Handbook of Health Economics. Elsevier Science, North-Holland, pp. 1003–1086.
García-Gómez, P., Schokkaert, E., Van Ourti, T., Bago d'Uva, T., 2015. Inequity in the face of death. Health Econ. 24 (10), 1348–1367.
Hersch, J., Pickton, T.S., 1995. Risk-taking activities and heterogeneity of job-risk tradeoffs. J. Risk Uncertain. 11, 205–217.
Hosseinpoor, A.R., Van Doorslaer, E., Speybroeck, N., Naghavi, M., Mohammad, K., Majdzadeh, R., et al., 2006. Decomposing socioeconomic inequality in infant mortality in Iran. Int. J. Epidemiol. 35, 1211–1219.
IBGE, 2008. Pesquina Nacional por Amostra de Domicílios (PNAD). In: IBGE (Ed.), Suplemento Saúde.
Idler, E.L., Benyamini, Y., 1997. Self-rated health and mortality: a review of twenty-seven community studies. J. Health Soc. Behav. 21–37.
Jones, A.M., Roemer, J.E., Rosa Dias, P., 2014. Equalising opportunities in health through educational policy. Soc. Choice Welfare 43 (3), 521–545.
Lefranc, A., Pistolesi, N., Trannoy, A., 2009. Equality of opportunity and luck: definitions and testable conditions, with an application to income in France. J. Publ. Econ. 93, 1189–1207.
Lugo, M.A., 2005. Comparing Multidimensional Indices of Inequality: Methods and Application. Society for the Study of Economic Inequality Working paper series.
Macinko, J., Lima-Costa, M.F., 2012. Horizontal equity in health care utilization in Brazil, 1998-2008. Int. J. Equity Health 11, 33.
Mackenbach, J.P., Kunst, A.E., 1997. Measuring the magnitude of socio-economic inequalities in health: an overview of available measures illustrated with two examples from Europe. Soc. Sci. Med. 757–771.
Mendes, Á., Marques, R.M., 2014. O financiamento da Atenção Básica e da Estratégia Saúde da Família no Sistema Único de Saúde. Saúde debate 38, 900–916.
Norheim, O.F., Asada, Y., 2009. The ideal of equal health revisited: definitions and measures of inequity in health should be better integrated with theories of distributive justice. Int. J. Equity Health 8, 40.
O'Donnell, O., van Doorslaer, E., Wagstaff, A., Lindelow, M., 2008. Analyzing Health Equity Using Household Survey Data: a Guide to Techniques and Their Implementation. World Bank, Washington, D.C.
O'Donnell, O.A., Van Doorslaer, E., Van Ourti, T., 2013. Health and Inequality.
Shorrocks, A.F., 2013. Decomposition procedures for distributional analysis: a unified framework based on the Shapley value. J. Econ. Inequal. 1–28.
Trannoy, A., Tubeuf, S., Jusot, F., Devaux, M., 2010. Inequality of opportunities in health in France: a first pass. Health Econ. 19, 921–938.
Van Kippersluis, H., Van Ourti, T., O'Donnell, O., Van Doorslaer, E., 2009. Health and income across the life cycle and generations in Europe. J. Health Econ. 28, 818–830.
Vasconcellos, S.C., 2013. A problemática do financiamento da atenção básica nos municípios no período do Pacto pela Saúde (2006-2010): o caso do Estado da Bahia. Faculdade de Saúde Pública. Universidade de São Paulo, São Paulo, pp. 158p.
Wagstaff, A., 2005. The bounds of the concentration index when the variable of interest is binary, with an application to immunization inequality. Health Econ. 14, 429–432.
Wagstaff, A., 2009. Correcting the concentration index: a comment. J. Health Econ. 28, 516–520 author reply 521-514.
Wagstaff, A., 2011. The concentration index of a binary outcome revisited. Health Econ. 20, 1155–1160.
Wagstaff, A., Watanabe, N., 2003. What difference does the choice of SES make in health inequality measurement? Health Econ. 12, 885–890.
Wagstaff, A., Paci, P., Van Doorslaer, E., 1991. On the measurement of inequalities in health. Soc. Sci. Med. 33, 545–557.
WHO, 2013. Global Health Observatory. (Geneve).
Yiengprugsawan, V., Lim, L.L., Carmichael, G.A., Dear, K.B., Sleigh, A.C., 2010. Decomposing socioeconomic inequality for binary health outcomes: an improved estimation that does not vary by choice of reference group. BMC Res. Notes 3, 1.