OVERALL UNFAIR INEQUALITY IN HEALTH CARE: AN APPLICATION TO BRAZIL

Estela Capelas Barbosa

PhD

University of York
Economics

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Abstract

The purpose of this thesis is to evaluate unfair inequality in healthcare use in Brazil, between 1998 and 2013, allowing for multiple social dimensions of inequality. The thesis innovates methodologically by proposing the Health Care Advantage (HCA) approach, which takes into consideration multiple social dimensions of inequality using a metric that is directly comparable to traditional bivariate measures that focus on a single dimension of inequality such as income. The thesis also has three other contributions. Firstly, it provides new empirical evidence about unfair inequality in health care in a developing country, where inequalities are particularly large and important. Secondly, it provides up-to-date national evidence about equity in the use of health care by analyzing a new wave of survey data in Brazil not previously analyzed. Thirdly, it provides the first national evidence about health care equity trends in mammography and cervical screening in Brazil, during a period of substantial health care reform. The data for the analysis comes from four large, repeated cross section sample surveys, the Health Supplement of the Brazilian National Household Sample Survey for the year 1998, 2003, 2008 and the first National Health Survey, conducted in 2013, with an average sample size of 371,000 over the four waves. After controlling for age, sex and self-assessed health, unfair inequality – or "inequity" – is observed in three different forms of care: physician visits, mammography screening and cervical screening. Overall inequity is substantially larger than income-related inequity. Over time, inequity has decreased for physician visits and cervical screening in Brazil, although for mammography there is no clear trend. Decomposition analysis shows that the main component of unfair inequality in all cases is health insurance, and its relevance increased between 1998 and 2013. For mammography and cervical screening, though not for physician visits, other key components of inequality (> 5% contribution) were region, urban status, education and income. Having children in the household was an important component of inequality in 1998, but this reduced substantially over time, as did the contribution of living in rural areas. The contribution of income to overall inequity decreased during the study period for physician visits and mammography screening, yet for cervical screening it doubled between 2003 and 2013. The methods developed in this thesis can yield useful new insights into unfair inequality in health care, and may help shift research attention away from income-related inequities that are not always the largest or most important inequities from a policy perspective.

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Author’s Declaration

I confirm that the work presented in this thesis is my own. I also declare that this thesis has never been submitted for any other degree at any other university or educational institution. The work contained here is original except for external sources of information which have been acknowledged and cited, and has not been previously published in full or in part.

The views expressed here are my own.

Versions of Chapters 4 and 5 have each been presented, at various stages of development, at the University of York's Health, Econometrics and Data Group Seminar Series. Papers based on Chapter 4 and Chapter 5 were discussed in the Health Economics Study Group Meeting in Glasgow, June 2014 and Manchester, January 2016 respectively, with Professor Richard Cookson as a co-author in both.

Chapter 1: Introduction

Health care systems are complex by nature. Several objectives guide actions of politicians and policy decision makers. These objectives include efficient resource allocation, achieving equity in the finance and delivery of services, improving quality and patient experience, and ultimately improving the health and wealth of the population (Morris et al., 2007, Marmot, 2013, Marmot, 2012). The present thesis is devoted to studying equity in health care use in Brazil.

Brazil is a middle-income country of large geographical dimension and a population of over 200 million inhabitants (IBGE, 2015). The Brazilian National Health System [SUS] was established in 1988 as a tax-based universal system and was the first formally to cover the healthcare of the whole population (Mendes and Marques, 2014). In terms of magnitude, in 2013, the system accounted for more than 56 thousand health care facilities, more than 350 thousand in-hospital interventions and nearly 500 thousand hospital beds (Brasil, 2013b).

In terms of inequalities in healthcare utilisation, traditionally, the economic literature has focused on socio-economic-related inequality (van Doorslaer et al., 1992, Van Doorslaer et al., 1997a, van Doorslaer et al., 2000, Bago d'Uva et al., 2009). This was mainly justified on the principle that inequalities in health (and health care use) should not be associated to socio-economic position, particularly in health care systems where the use of healthcare is free at the point of consumption (Wagstaff et al., 1991a). Furthermore, regardless of whether one defends equality of outcomes, equality of access or a capacity to benefit approach, researchers agree that inequality produced by socio-economic status is ethically objectionable (Culyer and Wagstaff, 1993). Finally, it has been recently argued that the focus on income can be justified as (a) it is a key policy concern, given the objective of decreasing socioeconomic divisions and (b) income-related inequality is easy to measure and interpret (Wagstaff and Kanbur, 2015).

Also more recently, authors have developed methods to account for multiple sources of inequality, which includes but does not focus exclusively on socio-economic status (Fleurbaey and Schokkaert, 2009, Fleurbaey and Schokkaert, 2011, García‐Gómez et al., 2014). In Brazil, previous studies have focused on income-related inequality (Macinko and Lima-Costa, 2012, Almeida et al., 2013) and have demonstrated that pro-rich inequality for physician visits exists. The research presented in this thesis substantially expands and updates these measures of inequality in Brazil. My objective is to provide a more comprehensive evaluation of unfair health care inequalities, allowing for multiple social dimensions and not just inequality related to a single social variable such as income. As the findings of this research will show, there are social variables that make a larger contribution to unfair health care inequality than income, including region, urban or rural status and education.

Furthermore, 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). If one considers private health insurance an unfair source of inequality, this variable alone is the largest contributor to overall unfair inequality. This implies that policy attention and action should be directed at those dimensions, and not just at income-related inequality, in order to reduce unfair inequality in health care.

As well as a literature review of the methods used to measure inequality in healthcare, and of relevant empirical evidence, the thesis has three empirical chapters and a conclusion. Chapter 4 is devoted to developing the methodological contribution, which I call the "Health Care Advantage" (HCA) approach, illustrated through an application to physician visits in Brazil in 2008. The HCA approach is a way of measuring overall unfair inequality that allows for multiple sources of inequality and also produces inequality indices that are directly comparable to the bivariate indices used in the standard literature on income-related inequality in health care, such as concentration indices, slope and relative indices of inequality, and simple inequality gaps and ratios. In this chapter, I show that measuring income-related inequality is just a special case of measuring overall unfair inequality, the case in which the only source of unfairness is income. I also show that, where multiple sources of inequality are considered, the measure of overall unfair inequality is substantially larger than income-related inequality in physician visits. This is to be expected, as income is only one component of overall unfair inequality. Factors making a larger contribution than income included private health insurance coverage and urban status; and factors making a smaller contribution include education and family type. Some of these factors are correlated with income, including education and private health insurance coverage, and so one can argue that factors relating to socioeconomic status in a broad sense made up the largest proportion of overall unfair inequality.

Chapter 5, in turn, is devoted to evaluating overall unfair inequality in two preventive cancer screening procedures for women: mammography and cervical screening. These are interesting variables to observe for a few reasons. First, they have been used in the literature as indicative of inequalities in health care for women in general (Moser et al., 2009, Lorant et al., 2002). Second, preventive care has wider macro-economic implications, insofar as it can potentially avoid women leaving the labour market or being unable to care for children or other members of the household (Marques et al., 2011a). Third, the process of allowing for need is relatively accurate and uncontroversial in the case of preventive procedures, since everyone within a certain age range is considered to need prevention and hence ascertaining the level of need does not require the use of hard-to-measure health variables. Hence a reasonable case can be made that the only relevant "fair" determinant of utilisation is age. Fourth, unfair inequality in cancer screening procedures has not been previously evaluated at national level in Brazil. Finally, mammography and cervical screening are inherently different forms of care: the former is capital-intensive and the latter is labour-intensive. As I explain in the chapter, this may help to explain some of the observed differences in patterns of unfair inequality between the two procedures. For mammography screening, for instance, inequality is not only larger in absolute terms, but region and urban residency appear to be an important factor contributing to inequality. This could be an indication of supply-side barriers to access. The fact is that most mammography equipment are located in urban areas of the South-East region of the country, which suggests that inequality could be decreased by increasing the supply of mammography equipment in other regions and rural settings.

In turn, Chapter 6 examines how the measures of overall unfair inequality for the three analysed forms of care have varied between 1998 and 2013. It shows that Brazil has managed to decrease overall inequality during this time for all three variables when observing the standard concentration index (CI) and the Horizontal Inequity index (HI) of overall unfair inequality. However, overall unfair inequality has increased between 2003 and 2013 according to Erreygers' Concentration Index (Erreygers, 2006, Erreygers, 2009) for mammography screening. The case of mammography is interesting, as it exhibits the largest unfair inequality and different patterns of change over time according to different indices. Brazil seems to have struggled to tackle inequalities in this capital-intensive procedure, and further inequality reduction may require changes in the geographical distribution of the MRI scanners and radiological specialists needed to perform and interpret mammography scans, alongside investment in additional publicly funded facilities within the SUS system The chapter also highlights that coverage by health insurance is becoming a more important factor contributing to inequality. For all three forms of care, health insurance coverage is the most important contributor to overall unfair inequality, and its relevance has increased over time.

In this thesis, I have used data from the Health Supplement of the National Survey (PNAD) for the years 1998, 2003 and 2008 and the National Health Survey for 2013. Both surveys are probabilistic complex designed and representative of the Brazilian population at national and sub-national levels. The empirical analysis was conducted as cross-sectional and in total over 1.5 million individuals were involved in the four waves of data.

In terms of contribution, the thesis innovates methodologically by proposing an approach that allows for multiple contributors to inequality, while retaining comparability with traditionally established bivariate indices of inequality that are familiar to decision makers and relatively easy to interpret. It also produces new knowledge about inequality in health care use in Brazil. The new knowledge does not only refer to the evaluation of preventive care for women and the focus on overall unfair inequality as opposed to income-related inequality, but also the use of a new wave of data only made available in 2015, which has not been previously used for measuring inequalities in health or healthcare. The first National Health Survey was conducted on the second half of 2013, after the Brazilian Institute of Geography and Statistics decided to separate the aspect of the survey for the National Household Sample Survey (PNAD).

The thesis has a number of limitations, including potential reporting bias and inaccurate adjustment for need for healthcare. Whereas each chapter discusses its own limitations and potential biases, one important one runs through the whole work: the lack of causal inference. At no point do I intend to imply that I can explain the causes of overall unfair inequality in Brazil. I merely observe the partial correlation of each variable towards overall unfair inequality, allowing for other variables. The decomposition measures I present represent associations between the factor and unfair inequality, not causal pathways. This thesis is about measuring unfair inequality in health care. Unpacking the causes and direction of unfair inequality in health care using structural econometric modelling is an important matter for future research that has not been contemplated in this thesis. The analysis performed in this thesis focuses on associations between variables, rather than causal links. No claims are made as to whether social variables such as income cause variation in health care use, or whether health care use causes variation in income and other social variables.

Finally, it is hoped that the results here presented may provide input for policy decision making. Previous inequality research has seldom resulted in concrete measures yielding policy relevant insights into ways of driving down the present inequality conditions prevailing in the Brazilian healthcare domain. It could be reasonably asserted that Brazil has been somewhat inept in using the available research on inequality in health care for informing policy driven action. The relationship between knowledge production and policy making within healthcare systems in Latin America is, at most, weak (Suárez-Berenguela, 2000). If equity is to be achieved, a more rigorous relationship should be formed between health policies and health research. Particularly equity research can be informative in providing evidence regarding the most deprived groups of society in terms of health care. It is, thus, important for research to contribute to policy making by incorporating more up-to-date methods and information that are simple and flexible enough to be effectively implemented as policy (Whitty, 2015, Culyer, 2001).

It is therefore hoped that the present work may help to shift the focus of researchers and policy makers in the health care domain from income-related inequality only to other important factors contributing to inequality. Income is an important source of inequality in healthcare, but its importance appears to be decreasing. Other factors such as health insurance, education, region and urban status also seem relevant. Region and urban status in particular may be correlated to the supply of resources within the health care system, indicating that some overall unfair inequality could be related to supply-side constraints. For mammography screening, for example, overall unfair inequality could be decreased if healthcare resources were more evenly distributed across the country. This type of action is within the realm of governments, both locally and nationally, and is likely to affect inequality directly. In addition, information and knowledge of how unfair inequalities in health care exist amongst groups is required to produce targeted policies that might drive down unfair inequality.

PART 1: LITERATURE REVIEW

Chapter 2: Methods for Measuring Inequality

2.1 Introduction

There is a long tradition of research by economists on measuring inequality in the distribution of income and wealth (Atkinson, 1970, Sen, 1973, Cowell, 1977). The basic tools of the trade are more than 100 years old: the American economist Max Otto Lorenz introduced the Lorenz curve in 1905 in his paper “Methods of measuring the concentration of wealth” (Lorenz, 1905), and the Italian sociologist and statistician Corrado Gini introduced the Gini coefficient in his paper on inequality in the distribution of wealth in 1912 (Gini, 1912).

Interest in measuring inequality in health and health care is more recent. However, over the past 20 years not only has the number of publications in this area increased exponentially, but its methods have also developed rapidly, allowing for more accurate measures and hence better information for policy makers (O'Donnell et al., 2008). Economists have developed better methods both for measuring inequality (O'Donnell et al., 2008) and for identifying the determinants or causes of inequality (Rosa Dias, 2009).

During the 1990s and 2000s, economic research on inequality in health and health care focused on “bivariate” measures of inequality. Bivariate measures are based on the relationship between two variables: a health variable and a single social variable considered to represent a source of unfair inequality, such as income. More specifically, the European Ecuity project team 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 (O'Donnell et al., 2008). Lately, researchers have started to examine “multivariate” measures of inequality, which allow simultaneously for multiple unfair sources of inequality in health. This more recent strand of research often draws explicitly on political and economic theories of equality of opportunity, which draw a 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). There is also a different strand of research on measures of “multidimensional” inequality, involving inequality in the distribution of multiple different goods – such as income, health, education and so on (Atkinson, 1982, Lugo, 2005).

This chapter devotes itself to reviewing methods for measuring inequalities in health and health care, as opposed to methods for measuring multidimensional inequality or methods for identifying the determinants of inequality. We start by reviewing key distinctions between different types of inequality measure – in particular, absolute vs. relative measures, extreme group vs. summary measures and univariate vs. bivariate vs. multivariate measures. We then review bivariate and multivariate measures in more depth, paying close attention to methods for adjusting for "fair" and "unfair" sources of inequality. By the end of the chapter, the reader should have a clear view of the range of possibilities in this field.

2.2 Key distinctions

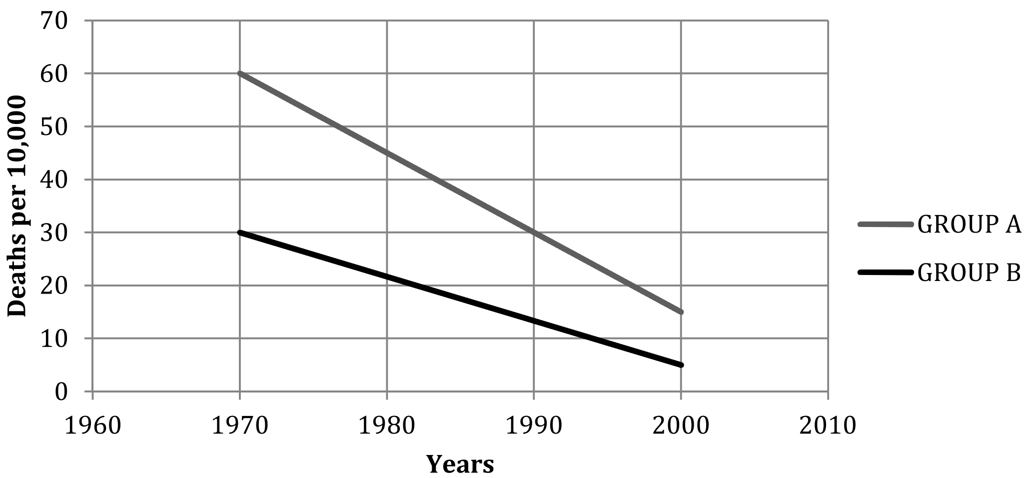
2.2.1. Absolute vs. Relative Measures

To introduce this distinction, we start by considering the simplest possible case of two individuals or groups. In this case, absolute inequality refers to the absolute difference in values between the two groups, whereas relative inequality is concerned with the ratio between the two groups.

These two concepts of inequality can yield entirely different results. For example, suppose amongst a population there are only two types of individual. The worse-off group has at time zero (t_0) an average income of £1,000 per calendar month (pcm). The better off have an average of £3,000. Later in time, such measures are retaken, and the new measures at time one (t_1) are now £1,500 and £4,500, respectively. In this example, it is straightforward to see that the income ratio between the groups has not changed (it remains three), whereas the absolute gap in values is now much larger than before (it has risen from £2,000 to £3,000). So in this case relative inequality is unchanged, but absolute inequality has increased.

Figure 2.1 shows a different example, this time applied to health inequality, in which relative inequality increases while absolute inequality decreases.

Figure 2.1 – Absolute vs. Relative measures of Health Inequalities



In the above figure, Group A could consist, for example, of less educated individuals, meanwhile Group B could be formed of more educated ones. Two things are immediately clear in the figure: i) the number of deaths amongst the population is lower for individuals with better education, and ii) in both groups the number of deaths per 100,000 of population has diminished from 1970 to 2000. In terms of absolute inequality, one may see that the absolute difference of 30 deaths per 100,000 inhabitants in 1970 has decreased to 10 in 100,000 by 2000. By contrast, in relative terms the ratios between Group A and Group B have increased from two (60/30) to three (15/5). Also one can see that Group A is obtaining a reduction in the number of deaths over time at a higher speed than Group B, which can be seen by the slope of the two curves.

Both examples illustrate how different concepts may yield different conclusions, and the importance of carefully considering which concept of inequality one is interested in. It can be argued that absolute measures of health inequality are generally more useful to social decision makers, since they give a better feel for the magnitude of the health problem in terms of physical units such as lives saved or diseases prevented – perhaps especially when the denominator is small or changes substantially over time as in the example above (Schneider, 2004).

We have chosen to exemplify each key distinction of inequality measurement using a 2-person example due to simplicity, but all examples can be extended to a multi-person case. The case above, for instance, instead of having Group A and Group B, we could have *n* groups or individuals. In case there are several groups or individuals, some properties for the measures of relative and absolute inequality are highly desirable (Asaria et al., 2012). They are:

1. Weak principle of transfers[1] – which requires the inequality index to increase when resources are transferred from worse-off to better-off individuals. The resources transferred may vary according to the inequality being measured, i.e. health in the case of health-inequality or income in the case of income-inequality.
2. Scale independence – valid for measures of relative inequality, which states that proportional changes in each individual's health should not affect the measure of health inequality.
3. Translation independence – valid for measures of absolute inequality, which advocates that equal absolute changes in individuals' health should not alter the measure of inequality.
4. Principle of population – which determines that health inequality should be invariant to the population size; and
5. Subgroup consistency and decomposability – which requires overall inequality to decline when inequality declines in one subgroup and remains the same in the rest of the population. Furthermore, decomposability means that the measure of inequality can be broken down

[1] This principle is an extension of the Pigou-Dalton transfer principle often relied upon in income inequality.

into the weighted average of the inequality existing within subgroups of the population and the inequality existing between them (Bourguignon, 1979).

The most frequently found measures of relative inequality in the literature are the Atkinson Index and the Concentration Index (Wagstaff et al., 1991a, Mackenbach and Kunst, 1997). This chapter will devote some space to explaining the later in detail, as it will be used in our empirical analysis. As to measures of absolute inequality, one often finds the Slope Index of Inequality (SII)[2] and the Kolm Index[3]. The literature has also addressed the difference in measuring inequality in shortfalls vs. achievement, for which the most common examples are health and ill-health (Kjellsson et al., 2015). Erreygers has provided insightful contribution to this matter, and will be discussed further in the following sessions (Erreygers, 2006, Erreygers, 2009).

2.2.2 Extreme group methods for measuring inequality.

Extreme group methods for measuring inequality, also known in the economic literature as 'gap measures', are simple to calculate and easy to interpret. Commonly, such measures only consider the two extremes of a population distribution, e.g. the first and last quintile or decile group, as they aim to highlight the situation of the poorer or worse-off. A good example of this type of measure can be given for Brazil, where the poorest 10% of the population receive only 1% of total GDP before tax but after transfers, whereas the richest 10% receive 47% of GDP (IBGE, 2008). In this case, it is obvious that the inequality between groups is huge (ratio1:47), but it is the policy maker's decision what to do with this information.

2.2.3 Summary methods for measuring inequalities

Summary measures look at the entire distribution of inequality between all relevant individuals or groups for which data are available. This avoids the potential arbitrariness of selecting two extreme groups for comparison, and gives a fuller picture of overall inequality. Various summary methods for measuring inequality have been developed in the past 20 years due to its relevance to both social and medical sciences – for example, univariate summary measures of inequality include the Gini coefficient, Atkinson index, Theil index, Kolm index and so on. The remainder of this chapter will devote itself to presenting the most important methods for measuring inequalities, starting with the well-known univariate method, i.e. the Lorenz Curve, going through the bivariate Concentration Curve and Index and finally, arriving at the regression-based

[2] For more information on SII, please see ASARIA, M., GRIFFIN, S., COOKSON, R. A., RICE, N., CLAXTON, K., CULYER, A. J. & SCULPHER, M. 2012. Univariate Assessment of Health Inequalities. *In:* ECONOMICS, C. F. H. (ed.). York: University of York..

[3] For more information on Kolm's absolute inequality index, please refer to ZHENG, B. 2007. Unit‐consistent decomposable inequality measures. *Economica,* 74**,** 97-111. and KOLM, S.-C. 1976. Unequal inequalities. I. *Journal of Economic Theory,* 12**,** 416-442..

multivariate techniques, which allow for the consideration of multiple sources of unfairness contributing to inequality.

2.3 Univariate methods

Univariate methods normally analyse how one particular characteristic or variable is distributed amongst a population. The most traditional univariate methods were developed in the late 19^{th}, early 20^{th} Century (Lorenz, 1905, Gini, 1912), although they are still relevant to social science studies nowadays. For the purpose of univariate inequality measurement, we will only describe in detail the Lorenz Curve, as it is most frequently found in the relevant literature.

2.3.1 Lorenz Curve

Since the publication of the "Atkinson Theorem" in 1970, the Lorenz curve has been a foundation for the analysis of welfare and inequality. Originally developed to understand income inequality in a population, it has also been extrapolated and used in the health and healthcare contexts. The Lorenz curve for income plots the cumulative share of sum total income on the y-axis, with individuals ranked from poorest to richest on the x-axis. Two distinctions are important here: (a) the Lorenz curve only deals with cardinal variables, that is, it must be possible to add up the variable to yield a meaningful sum total, for calculating the cumulative share of the total on the y-axis and (b) since individuals are ranked in relative terms on the x-axis the standard Lorenz curve is only useful when measuring relative inequality. Point (a) can be problematic in relation to health, since many individual level health variables – such as self-reported health, or the presence of death or disability – are measured on an ordinal rather than cardinal scale. On point (b), there is also a "generalized" Lorenz curve that can handle absolute inequality, as described below.

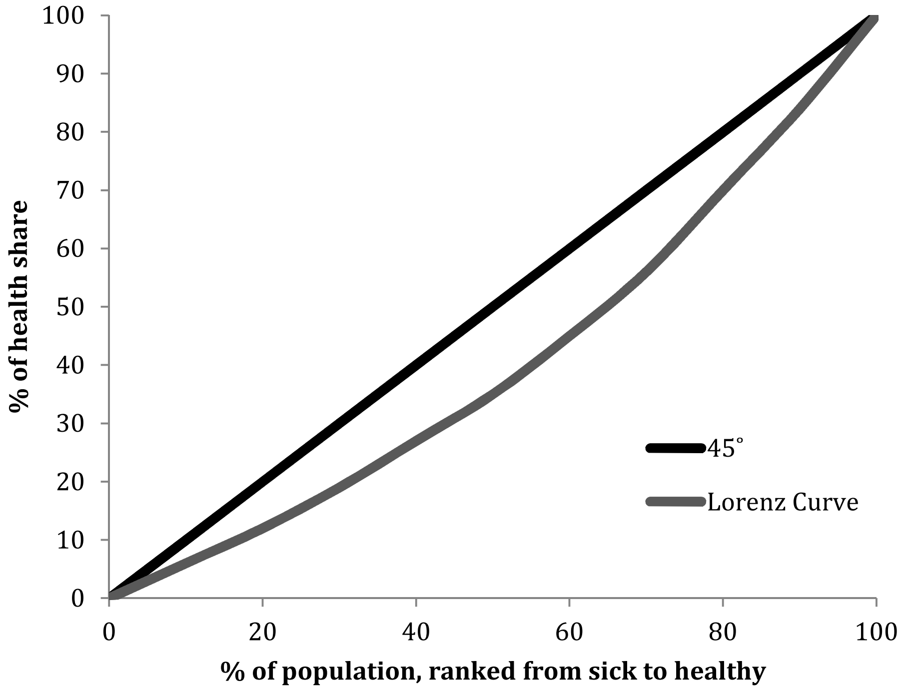
The measure of relative inequality that follows most naturally from the standard Lorenz Curve is the (relative) Gini index, which is given by twice the area between the plotted Lorenz Curve and a 45˚ line of equality. Mathematically, for the traditional case of income distributions, it is given by:

$$G = \frac{2\,\mathrm{Cov}\,(y, F(y))}{\mu_y} \qquad [1]$$

where y is income, F(y) is the cumulative distribution function of income and μ_y is the mean level of income across the population. There is also an analogous absolute Gini index for computing absolute inequality, based on the generalized Lorenz curve, which will be explored in more detail below.

In general terms, the goal of the standard Lorenz curve is to demonstrate how a cardinal variable is distributed [or shared] among a certain population (Lambert, 2001). Figure 2.2 shows a standard Lorenz curve for health. As in the traditional Lorenz curve, the 45˚ line in figure 2.2 is the perfect equality line, that is, if every individual had its fair share of health the Lorenz curve would be on the 45˚ line and there would be no inequality. The curve below it, the Lorenz curve, represents how health is distributed amongst the population. Given that the ranking of individuals goes from the sickest to the healthiest, the Lorenz curve must be equal to or below the equality line. In the case of the latter, the sicker segments of this sample population get less than their fair share of health, whereas the healthier segments get more than their fair share.

Figure 2.2 – Lorenz Curve applied to health



In turn, the absolute Gini index can be derived from the generalized Lorenz Curve, as introduced by Shorrocks (1983). Whilst the standard Lorenz curve shows each individual's relative share of resources, the generalized Lorenz curve shows each individual's absolute short-fall or surplus compared with society's mean level of resources. For the traditional case of income, the absolute Lorenz curve is obtained by multiplying the standard Lorenz curve by mean income. In the words of Moyes, "it represents the average income short-fall of the (k/n) x 100% poorest individuals, i.e. the average income that would be necessary in order to provide to any one of them the society's mean income", where n is the total number of people and k the individual's position in the income rank (Moyes, 1987).

The corresponding measure of inequality is the absolute Gini, which is sensitive to variations in the mean value of the resource for which inequality is being measured. Mathematically, for the case of income, the absolute Gini is defined as:

$$AG = \mu_y G \quad [2]$$

where μ_y is the mean income and G the relative Gini coefficient defined in equation [1].

The sensitivity to the mean of the absolute Gini coefficient implies that comparison between countries or time periods with different means is less straightforward (Araar, 2006). The fact that relative indices of inequality are independent of the unit of account may, to some extent, explain the more widespread use in the literature of the relative Lorenz curve as opposed to the absolute Lorenz curve.

2.4 Bivariate methods

As the name suggests, bivariate methods take into account two features of certain (groups of) individuals – a health (or health care) variable, and a social variable, such as income, race, gender, educational status, etc.

Generally speaking, one can divide social variables into two main types: (a) variables from which a natural ordinal ranking can be produced from less to more advantaged, such as occupational class, education, income and wealth; and (b) variables with no natural rank order, including binary and multinomial variables, such as geographic location, ethnicity and gender. Although some inequality comparison is possible in the latter group of variables, traditional bivariate measures such as the concentration index are most useful when applied to social variables that can be ranked (Van de Poel et al., 2012). In other words, for the application of bivariate methods of measuring inequalities, the health variable must be cardinal, whereas the social variable only needs to be ordinal.

2.4.1 Concentration Curve

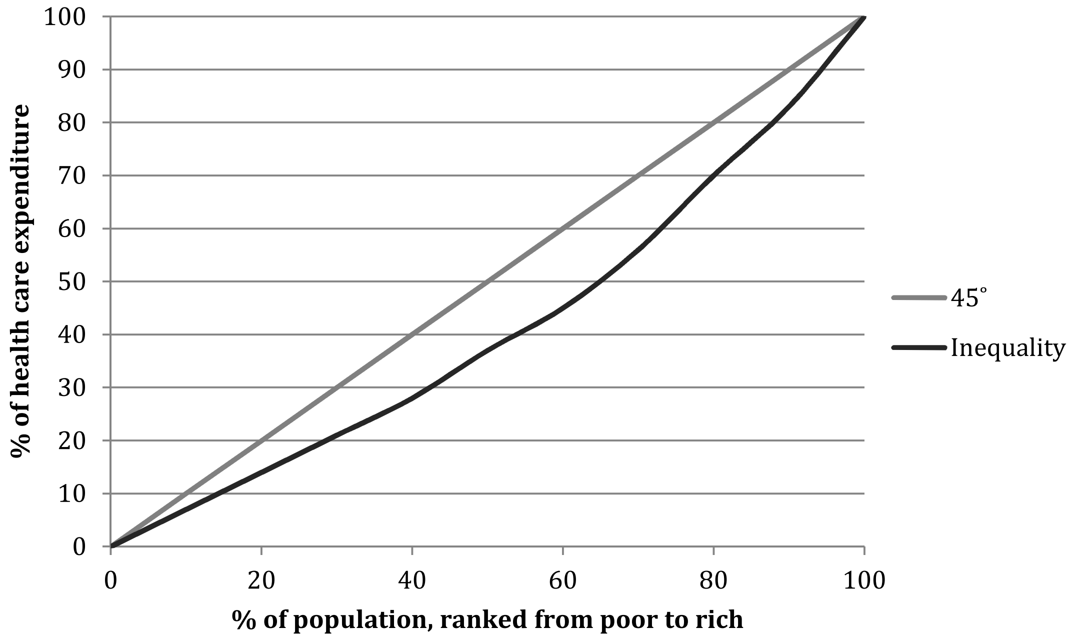
The concentration curve is perhaps the most well-known and most often applied method for measuring inequalities in health and healthcare, in particular for assessing socioeconomic-related inequality (O'Donnell et al., 2008). From the concentration curve one can calculate the concentration index, which will be discussed in more detail in the following section. Its definition is analogous to that of the Lorenz curve[4]. As in the Lorenz curve, the concentration curve is built by plotting the cumulative proportion of a health (or healthcare) variable against the cumulative proportion of the social economic variable. In order to build both the Lorenz and the Concentration curves, one may either use individuals as the unit of analysis, or groups, taking the mean values across groups of individuals. Figure 2.3 shows two examples of concentration curves for health

[4] If the expected health variable is strictly monotonic in income, the ranking of such expected variable (E[h/y]) is equal to the ranking of the comparison variable (y). In this case, the concentration curve and the Lorenz curve are the same, so long as the concentration curves only uses health and the population is ranked in a health parade, that is, from sickest to healthiest.

care, where individuals are the unit of analysis.

Figure 2.3 – Concentration curves applied to health care

(a)



(b)

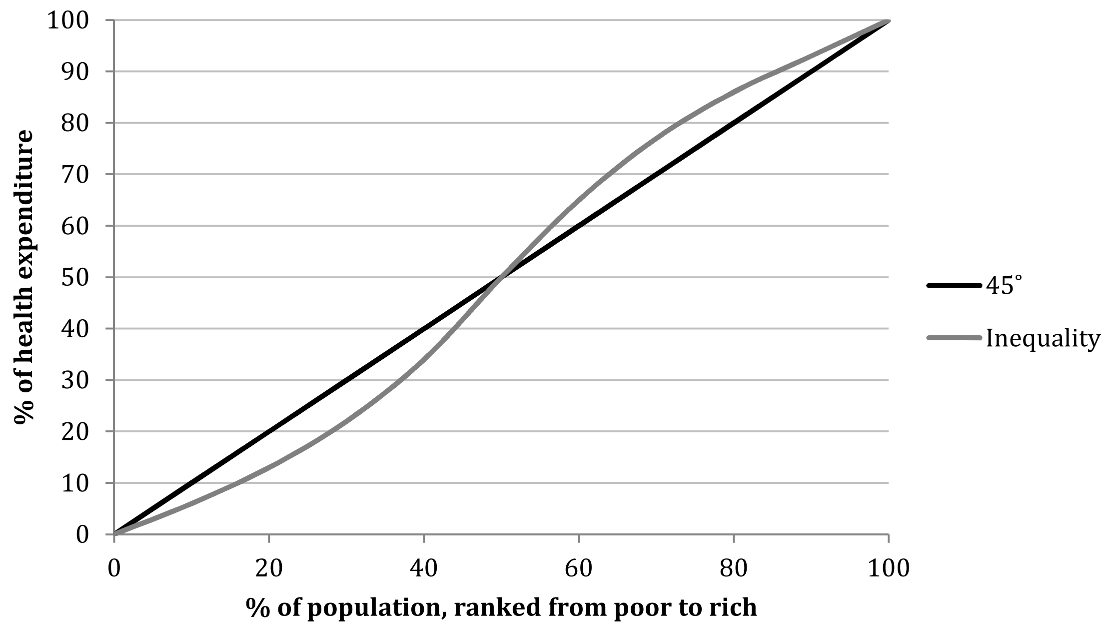


Figure 2.3 demonstrates an important concept in the concentration curve framework, that of dominance. It is said that the concentration curve dominates the equality line if it lies significantly

above it, which implies a concentration of the observed variable amongst the poor. In the opposite direction, the equality line dominates the concentration curve if it lies above it, as in Figure 3 (a). Dominance can also be tested between different concentration curves, so different years or groups may be compared.

As far as dominance is tested, two results are possible: i) non-dominance, if the null hypothesis for equality is not rejected; ii) dominance, if equality is rejected. In basic terms, if a distribution A dominates a distribution B, then distribution A is less unequal in terms of relative inequality. If the curves cross, there is no clear dominance, given that there is at least one significant difference in each direction, although it is possible that the null hypothesis of equality is still rejected. This latter case must be analysed more carefully, as the inequality varies along the population distribution. In theory, the use of different value judgments to classify dominance implies the possibility of different final classifications, as it depends on the definition of the null hypothesis for equality. This has been observed in the literature, for example, with regards to the difference in inequality that focuses on shortfall versus achievement (Kjellsson et al., 2015). In addition, dominance (and non-dominance) can be tested statistically and different statistical approaches can also produce different conclusions (Davidson and Duclos, 2000, Barrett and Donald, 2003, Anderson, 1996) [5].

In practice, the case of non-dominance means that where a controversial value judgement is in place, researchers should not rely exclusively on the concentration curve and consequent index, but possibly look at inequality in other forms of reporting. One difference in value judgement relates to the concepts of dominance proposed by Atkinson and Shorrocks, respectively. Atkinson's theorem on dominance holds true when the mean health of a (relatively) more equal distribution is equal or greater than the mean health of a less equal distribution. In that case, a 'win-win' situation can be found, as dominance exists, as the more equal health distribution also has equal or greater overall mean (Kobus, 2012). Shorrocks' theorem on dominance, on its turn, aims to take into consideration that decision makers are generally income-seeking and risk averse (Bellu and Liberati, 2005). It establishes that one would never prefer a more equal distribution with lower overall mean, implying that equality is not preferred in case of lower overall means. Atkinson's and Shorrock's positions on dominance exemplify different normative assumptions, and it is possible to find Atkinson dominance and no Shorrocks dominance when comparing two distributions (Asaria et al., 2012).

Case (b) above, therefore, is a case of non-dominance due to curves crossing, as there are significant differences in both directions. When the dominance is not as clear, the decision rule

[5] For more on statistical testing of dominance see COWELL, F. A. & FLACHAIRE, E. 2013. Statistical methods for distributional analysis. *Handbook of Income Distribution,* 2**,** 359-465.

stipulates that there must be at least a significant difference in one direction between the curves and no significant difference in any other (O'Donnell et al., 2008).

2.4.2 Concentration Index

The concentration index (CI) is generally considered a summary measure of socioeconomic-related inequality in health or health care. Graphically it is easy to see, as it consists of twice the area between the concentration curve and the 45˚ line. Its interpretation determines that if the value of the index is negative, there is a concentration of the variable analysed amongst the poor or worse-off.

Mathematically, the Concentration Index can be defined by the following formula, where N is the population size, h_i is the health status, μ_h is the mean health and r_i is the rank position in the distribution of the ranking variable, normally the distribution of income.

$$CI = \frac{2}{N\,\mu_h} \sum_{i=1}^{n} h_i\, r_i - 1 - \frac{1}{N} \qquad [3]$$

Two methods are normally used for estimating the concentration index: i) the covariance method and ii) the regression method. Although computed in different ways, they both result in an index that ranges from -1, when the poorest or worse-off person has all the health variable; to 1, when the richest or better-off person has the totality of the variable. Some academics (Wagstaff and van Doorslaer, 2000a, van Doorslaer et al., 2000, van Doorslaer et al., 1997b) consider that when interpreting a concentration index the direction (positive, negative or null) is often more important than the magnitude itself, since the latter is not so meaningful when considered in isolation. Even if the magnitude of the Concentration Index is difficult to interpret on its own, however, it can still be useful for comparative purposes (Haque, 2006). Several studies in high-, middle- and low-income countries have been conducted using this index to make inequality comparisons (Van Doorslaer and Koolman, 2000, van Doorslaer et al., 2000, Van Doorslaer and Masseria, 2004, d'Uva et al., 2009, Devaux and De Looper, 2012, Rossi et al., 2009, Suárez-Berenguela, 2000).

2.4.3 Corrections to and Extensions of the Concentration Index

Even though the Concentration Index is a useful summary measure of health inequality, it basically depends on the mean of the health variable (Wagstaff, 2005) and on measurement properties of the health variables (Erreygers, 2009), making it inappropriate for use with ordinal health variables – including binary variables (such as mortality, or whether self-rated health is good or very good, or whether a particular form of health care has been used) – or even for bounded cardinal variables. To solve some of those issues, some modifications have been proposed to the CI for use with binary variables, resulting in the normalization and standardization of the index.

The Erreygers Index is a modified Concentration Index (Erreygers, 2006) that satisfies the mirror, monotonicity and transfer properties, as well as encompassing a cardinal consistency and a level of independence. The mirror property determines that a scale invariant rank-dependent index I is the same for a "positive" health variable (e.g. survival) as for its mirror opposite "negative" illness variable (e.g. mortality). That is:

$$I(h) = -I(s) \qquad [4]$$

For a binary variable, this property holds if, and only if:

$$g(\mu_x,n) = g(1-\mu_x, n) \qquad [5]$$

where g is a function that depends on both μ_x - the mean of the distribution and n - the population size. Mathematically, the Erreygers concentration index is defined as stated in equation 6, where b_h and a_h are the maximum and minimum values of the health or healthcare utilisation variables.

$$E\left(h\right) = 4\frac{\mu}{b_h - a_h} CI\left(h\right) \qquad [6]$$

Although the index proposed by Erreygers has some useful properties, it is sensitive to the mean in a way that implies the index is not a relative measure but rather is a quasi-absolute measure of inequality (Wagstaff, 2011a). For binary outcomes, for example, where b_h and a_h are 1 and 0, respectively, higher means result in a higher index. This is a normative judgement, as Erreygers feels that if more people on the upper part of the distribution are receiving care, for example, inequality is larger (Wagstaff, 2011a, Wagstaff, 2011b, Kjellsson et al., 2015). In the words of Wagstaff:

> Erreygers gives an example of a population of 100 persons where the 10 richest persons initially have maximum health and all the rest have minimal health. There is then a change in which the second 10 richest people also acquire maximal health. In the case of a binary variable, the concentration index registers a reduction in inequality. Erreygers argued, however, that the second distribution is 'clearly' more pro-rich, on the grounds that '10 rich persons are now in better health, whereas everything else remains the same'. [...] but it could be argued—and contrary to Erreygers' suggestion—that the second distribution is less pro- rich than the first, on the grounds that the privilege of being healthy is not quite so dramatically associated with being rich as in the first. That is, of course, what the concentration index concludes. I have some sympathy with this view (Wagstaff, 2011a).

In turn, the generalized Concentration Index (Wagstaff, 2005) is obtained via the generalized concentration curve, which is analogous to Shorrock's generalized Lorenz curve

(Wagstaff et al., 1991a). Also known as the GCI, it is essentially the CI divided by one minus the mean of health, μ_h. Hence, it is obviously sensitive to the mean value and basically implies that gains in mean health should be traded-off for increases in pro-rich inequality, in other words, decreases in the health values of the better off are acceptable if it is for the gain of the mean health. Again, this is a normative judgment, as it expresses a view on inequality. According to the author himself, the correct interpretation of the generalized Concentration index is conditional to the mean (Wagstaff, 2011a).

Finally, an extended concentration index has been developed (Wagstaff, 2002, Wagstaff et al., 2003) to allow for different degrees of inequality aversion. The original (or standard) concentration index implies that weights are linearly distributed by fractional rank from -1 to 1 from the poorest / worse-off to the richer / better-off. This means that the health status of an individual is weighted according to his/her position in the rank, reaching a number close to zero for the richest person. In other words, the standard CI places more weight to transfers affecting the middle of the income distribution (Atkinson, 1970). On the other hand, the extended Concentration Index permits health to be weighted equally amongst the population; for individuals at the higher end of the distribution to have a positive weight on health and for non-linear distribution of weights. This permits researchers to take different views on inequality aversion and forego the constant (relative) inequality aversion implied by the standard CI (Wagstaff, 2002, O'Donnell et al., 2008).

All three extensions to the CI described above impose the principle of income-related health transfers, by which “transferring health from someone who is better-off in terms of socioeconomic status to someone who is worse-off in terms of socioeconomic status does not lead to a reduction in social welfare provided the transfer does not change the ranking of the individuals in terms of socioeconomic status” (Bleichrodt and Van Doorslaer, 2006).

Finally, each of the indices and modifications mentioned previously imply a different set of normative perceptions, as discussed, towards which a researcher may be more or less inclined depending on the question being addressed. The (unstandardized) standard CI, for instance, is more in line with the equality of outcomes philosophy, given that, in practice, it is bounded between μ_h-1 and 1- μ_h. This implies that in a hypothetical distribution where $\mu_h = 1$, plausible in the case of healthcare where all individuals receive care, but less so in the case of health, CI = 0, although unfairness regarding the amount of care received might still exist. Nonetheless, there is in the literature an intense debate to establish which (if any) of the existing indices is the most appropriate for each circumstance. Particularly a lot of attention has been given to binary outcomes, as they are often used in health and healthcare (Wagstaff, 2011a, Wagstaff, 2011b, Erreygers and Van Ourti, 2011b, Erreygers and Van Ourti, 2011a, Kjellsson and Gerdtham, 2013).

2.4.4 Standardization of Bivariate Methods

So far we have described the concentration curve and index without looking at their most common potential pitfalls. First, in the application of bivariate methods, the variables in use might have some correlation that is not considered in the model and might, thus, contaminate the obtained results. For example, suppose one wants to observe the relationship between income and health, both for men and women. It is expected that the higher the income, the healthier the population, regardless of sex (i.e. positive effect of income on health). Nonetheless, it is also true that women are, on average, healthier and poorer than men. It is quite straightforward to see that one may misleadingly underestimate the importance of income on health inequality. That derives from the fact that the average health of the better off will be smaller than that of the worse off, simply as a result of a diminished proportion of healthier women amongst the rich (Gravelle, 2003). Therefore, in cases such as this, it is important to control for the confounding factor, that is, those which cause the misleading inference (Van Doorslaer and Koolman, 2000).

There are two different ways of controlling for confounding factors, namely, i) direct standardization and ii) indirect standardization. Direct standardization corrects the distribution of health (or healthcare) by creating an artificial distribution in which the standardizing variables are held constant across all individuals, but allows non-standardizing variables to behave as in the original distribution. In a simple case, where health is only a function of income and age, direct standardization would produce a distribution of health in which age is held constant but income is allowed to vary (O'Donnell et al., 2008). Direct standardization is usually applied using grouped data (Wagstaff and Van Doorslaer, 2000b), but as Gravelle (2003) has demonstrated it can also be performed with individual level data. Using a convenient regression, direct standardisation may be calculated as follows. In a simple linear health regression model:

$$h_i = \beta_0 + \beta_y\, y_i + \beta_a\, a_i + \varepsilon_i \qquad [7]$$

where h_i is the health of individual i, y is income, a is age and ε the error term, the directly standardised health function would be given by:

$$h_{i\_direct} = b_0 + b_y\, y_i + b_a\, a_{ref} \qquad [8]$$

where the variable age is held at a reference value and b_j are the estimated values of the true population parameters β_j, defined in equation 7. The directly standardised concentration index of health is then given by the formula:

$$CI_{direct} = \frac{2\,Cov\,(h_{i\_direct}, F(y))}{\mu_h} \qquad [9]$$

where h_{i_direct} is the directly standardised health, F(y) is the cumulative distribution function of income and μ_h is the mean level of health across the population, based on the original health function. In case the mean values of observed health and directly standardised health in equations [7] and [8] respectively coincide (i.e. $\mu_h = \mu_{hdirect}$), then the directly standardised concentration index of health is equivalent to the concentration index of directly standardised health.

The directly standardized concentration index may also be expressed as a function of the Gini coefficient. In that case:

$$CI_{direct} = \frac{b_y \mu_y}{\mu_h} G \qquad [10]$$

where b_y is the estimated regression coefficient of income from the directly standardised health function (equation 8), μ_y is the mean level of income across the population and μ_h is the mean level of health.

Indirect standardisation, on the other hand, corrects the effects of standardising variables like age by comparing the original distribution to one in which only the standardising variables influence the outcome and the influence of non-standardising variables has been removed by setting the non-standardising variables at reference values so that they have the same mean effect across all individuals. Once again, in our simplistic example of health as a linear function of income and age, this would imply allowing age to vary whilst holding income at a reference value. Mathematically, using the same health linear regression model as defined in 7, one can use a convenient regression to predict:

$$h_{i\_agepredict} = b_0 + b_y y_{ref} + b_a a_i \qquad [11]$$

Equation 11 defines the age predicted health function, which in turn is used to determine the indirectly standardised health function.

$$h_{i\_indirect} = h_i - h_{i\_agepredict} + \mu_h \qquad [12]$$

The indirectly standardised concentration index is given by:

$$CI_{indirect} = \frac{2 \text{ Cov } (h_{i\_indirect}, F(y))}{\mu_h} \qquad [13]$$

Alternatively, the indirectly standardised concentration index can be expressed as:

$$CI_{indirect} = CI - CI_{agepredict} \qquad [14]$$

where the CI is the concentration index of the unstandardized (original) health function and the $CI_{agepredict}$ is the concentration index of the predicted health function described in equation 11.

Our example is simplistic and equation 11 is usually more complex, for example involving complications such as multiple standardising variables, non-linear functional forms for standardising variables like age and non-linear regression models for categorical health variables. Furthermore, for non-linear regression models, the choice of reference value is particularly important, given that the resulting marginal effects will depend on such reference value (Hosseinpoor et al., 2006, Yiengprugsawan et al., 2010). Equation 14 is also the definition of the (conventional) horizontal inequity index (HI), which calculates the measure of inequality straight from equations 7 and 11, without going through the steps explicated by equations 12 and 13.

Some authors (Kakwani et al., 1997, Wagstaff and Van Doorslaer, 2000b, Van Doorslaer and Koolman, 2000) suggest that indirect standardization is a simpler and more convenient method for removing the confounding effects of standardising variables on health. Other authors favour direct standardization, arguing that this method provides a more consistent estimator of the concentration index (Gravelle, 1998, Dusheiko and Gravelle, 2001, Gravelle, 2003)..

2.5 Multivariate methods

So far we have concentrated on approaches that focus on two variables at a time – a health care variable and a single social variable deemed to represent an unfair source of variation in health care. We are now interested in models which take into consideration more than one unfair source of inequality, and thus are known in the equity literature as "multivariate methods". In the equality of opportunity literature, where the focus is generally on outcomes such as income or health rather than the use of services such as health care, inequalities are considered fair or legitimate if they derive from natural circumstances (e.g. demographics) or are a result of choice (e.g. lifestyle), from which an individual is considered responsible. In contrast, illegitimate or unfair sources of inequality include any circumstance that lies beyond the individual's control, including parental endowments, physical environment, access to health care services, and so on (Fleurbaey and Schokkaert, 2009). In terms of health care, the duality of choice and circumstances is not the only relevant factor to be taken into consideration. The key issue for defining whether inequalities are fair or unfair are the need for services (Cookson et al., 2016). Indeed some authors defend that, where multivariate methods are used, both total and unfair inequalities should be measured, as they allow for the identification of different needs in terms of equity-focused health policies (Asada et al., 2015).

2.5.1 Inequality of Opportunity Framework

The earliest approach in health economics for modelling inequality of opportunity was proposed by Roemer (Roemer, 1993, Roemer, 1998, Roemer, 2002) and considers that a person's advantage or success (y_i) is determined by a vector of illegitimate factors, the circumstances (c_i)

and a vector of legitimate factors, the effort (e_i). This framework takes as given the existing level of productive technology (Fleurbaey and Schokkaert, 2011).

$$y_i = y\ (c_i, e_i) \qquad [15]$$

In this terminology, two individuals at the same level of effort should obtain the same degree of success, otherwise inequality of opportunity exists. Roemer's original model establishes a monotonic relationship between health and the variable(s) of interest to define the individual's rank position in the distribution, but this is only one possible approach, and several others have emerged in the literature (Fleurbaey and Schokkaert, 2011). Nonetheless, the general focus on distinguishing between "circumstances" and "effort" remains.

Consistent with the economic rationale of utility maximization, Fleurbaey and Schokkaert have proposed a model in which an individual's health is determined by his/her medical consumption (m_i), consumption goods (c_i), including lifestyle (e.g. smoking), the genetic health endowment (e_i), a stochastic health shock (ε_i), job characteristics (o_i), including leisure and social background (s_i) (Fleurbaey and Schokkaert, 2009).

$$h_i = \mathrm{H}\ (m_i, c_i, e_i, \varepsilon_i, o_i, s_i) \qquad [16]$$

In this model some variables within the categories can be considered circumstances, whereas others may be regarded as effort, and others can be considered as being determined by a combination involving both circumstances and effort. Job characteristics are an example of the latter. That is, someone's job characteristics may be at least partly determined by this person's level of education, which might be considered a circumstance insofar as a child has limited responsibility for parental decisions about which school to attend. Though on the other hand, job characteristics may also partly reflect choice and effort in terms of investments of time in career development rather than leisure. Given a budget constraint, the health outcome for the individual *i* will be a result of a multiple equation maximization problem.

2.5.2 Direct Unfairness and the Fairness Gap

In an equality of opportunity framework, one of the central issues is how to move from the measurement of overall inequality to unfair inequality only. Two methods have been proposed to resolve this issue, namely i) direct unfairness and ii) the fairness gap (or ratio). Direct unfairness involves direct standardization for "legitimate" or "fair" sources of inequality, while the fairness gap (or ratio) involves indirect standardization for "legitimate" or "fair" sources of inequality.

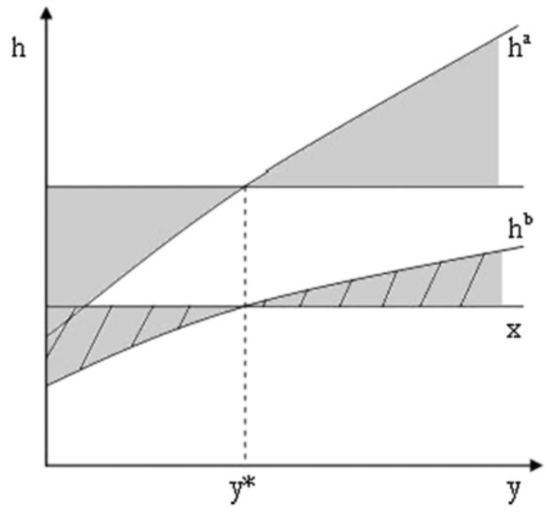
In general terms, direct unfairness is based on the idea that "a measure of unfair inequality should not reflect legitimate variation in outcome, i.e. inequalities which are caused by differences in responsibility variables" (Fleurbaey and Schokkaert, 2009). In other words, legitimate differences should not influence the inequality outcome. This technique, also known as conditional equality, eliminates the legitimate (or "fair") sources of inequality by setting them at a reference value to correct the outcome value for their influence. In other words, it builds an artificial distribution, in which everyone, counterfactually, is assumed to have the same level of the legitimate variables – e.g. "effort" or "need" variables – and hence the influence of these variables is purged.

By contrast, the fairness gap is based on the principle of compensation. In other words, if the unfair inequality measure is zero, all inequality observed may be considered fair. According to the authors, the fairness gap is based on the idea that when or if a "measure of unfair inequality is zero, there should be no illegitimate differences left" (Fleurbaey and Schokkaert, 2009). As a result, two people with the same value for legitimate variables (e.g. "effort" variables for which they can be held responsible) should obtain the same outcome (in our example, the same value for health).

Direct unfairness and the fairness gap clearly follow from the standardisation methods described earlier. Whilst direct unfairness is analogous to direct standardisation, the fairness gap bears similarities with indirect standardisation. Because the two approaches deal with illegitimate sources of inequality in slightly different ways, they do not necessarily yield the same results. In particular, in models with interactions or non-linearities, direct unfairness and the fairness gap yield different results. The picture below illustrates. In fact, the measures of direct unfairness and the fairness gap only yield the same results if the specified health function does not have interactions and is additively separable for the absolute case, and multiplicatively separable for the relative case. The following example may help elucidate.

Suppose we are looking at two groups of individuals (Group A and B) with different lifestyles. Group A is composed of "healthy lifestyle" individuals (e.g. people who are non-smokers, with a healthy diet etc.) and can be considered healthier overall. Let h^a be the health function for group A and h^b the function for group B, in terms of a variable y deemed to represent an unfair source of health inequality, such as income. The measurement of direct fairness is done by fixing a lifestyle reference value – in this case, setting both Groups equal to the "unhealthy lifestyle" reference value of Group B – which yields a health of x at the mean income value of y*. Comparing the distance between the curve for Group B and the reference line x will then give us a "direct unfairness" measure of inequality. In the figure, if we focus on group B, the striped area gives us a "direct unfairness" measure of inequality (Fleurbaey and Schokkaert, 2009).

Figure 2.4 – Direct Unfairness and Fairness Gap



Source: Fleurbaey & Schokkaert, 2009.

Using direct unfairness as a measure of inequality has the pitfall of neglecting the unfairness existing for group A, in fact it fully neglects the inequality implicit to lifestyle A. Implicitly using direct unfairness to measure inequality implies the neutralisation of the effect of lifestyle differences, translated in the difference slopes of h^a and h^b. In the fairness gap measure, on the other hand, we would fix a value *y* – in this case, the mean income of y* - and then take into account each individual difference, that is, calculate the gap between the individual's actual health status – a point on the curve h^a or h^b - and the health status she or he would achieve if all income differences were removed. For the fairness gap, the shaded areas of the chart represent the size of inequality. Nonetheless, the fairness gap has the pitfall of taking into consideration the difference in slopes of each group, whereas ideally, we would like to neutralize such effect.

2.5.3 General Framework applied to health care

Although the framework previously explained can be applied to health and health care, due to the nature of the empirical work to follow, the application for health care requires further consideration.

Consider a health care function in the form hc(*u*, *f*), where *f* denotes fair variables, and thus only produces legitimate inequalities in health care, and *u* corresponds to unfair variables, which bring about ethically objectionable inequalities. In this case, a general formula for the health care function states:

$$\mathrm{h}c_i = \mathrm{h}c\ (N_i, P_{i,} SES_\mathrm{i}, Z_{i,;} X_i) \qquad [17]$$

In this function N_i stands for health care needs, which depends on socioeconomic status, demographic variables and lifestyle preferences. The model also establishes that health care is also a function of differences in treatment preferences (P_i). Z_i are other variables considered "unfair", and X_i are neutral variables considered neither fair nor unfair.

Traditionally, the socioeconomic inequality literature assumes that $u = SES$ and $f = (N)$. This approach, however, has the disadvantage of disregarding other "unfair" sources of inequality and of disregarding one potential "fair" source of inequality i.e. treatment preferences. Thus, as Fleurbaey and Schokkaert have proposed, it may be more interesting considering $u = (SES, Z)$ and $f = (N, P)$ (Fleurbaey and Schokkaert, 2011). Nonetheless, the proposed method has the advantage of flexibility, while considering $u = SES$ is only one possible ethical approach. Several other normative decisions regarding which variables to place under the fair or unfair vectors are possible.

The measure of individual advantage can be used to obtain a measure of illegitimate inequality. The same methods of fairness gap and direct unfairness previously described for health can be calculated for the health care case. For the fairness gap, when measured in absolute terms, that is, when specified to calculate absolute inequality, one needs to establish a reference value for all unfair variables, be it socioeconomic status (SES) or other variables (Z). One natural way of doing this is to choose the socioeconomic status that is considered to receive treatment the best possible way, or that is closer to the optimal health care value. Obtaining the fairness gap distribution can then be done using a convenient regression, in which one predicts healthcare use ($hc_{i\_predicted}$) holding all unfair and neutral variables at a reference level. In such case, the fairness gap will be given by:

$$hc_{i\_fg\_a} = hc_i - hc_{i\_predicted}\,(N_i,\ P_i, SES_{ref}, Z_{ref}, X_{ref}) \qquad [18]$$

Given that in our empirical application, variables are either deemed fair or unfair, no neutral variables (X) are in place. This implies that equation 19 may be reduced to:

$$hc_{i\_fg\_a} = hc_i - hc_{i\_predicted}\,(N_i,\ P_i, SES_{ref}, Z_{ref}) \qquad [19]$$

If one wishes to measure relative inequality, then the formula for the fairness gap, in its reduced form, is given by:

$$hc_{i\_fg\_r} = hc_i \,/\, hc_{i\_predicted}\,(N_i,\ P_i, SES_{ref}, Z_{ref}) \qquad [20]$$

Turning our attention to direct unfairness, one could evaluate the advantage or disadvantage of individuals using a convenient regression to predict healthcare use fixing all variables that derive from preference and needs, as well as neutral variables. In this case, we would obtain the measure of direct unfairness:

$$hc_{i\_du} = hc_{i\_predicted}\ (N_{ref},\ P_{ref}, SES_i, Z_i; X_{ref}) \quad [21]$$

Like before, for purposes of application in our empirical chapters, considering that no variables are deemed neutral in the analysis performed, equation 22 may be reduced to:

$$hc_{i\_du} = hc_{i\_predicted}\ (N_{ref},\ P_{ref}, SES_i, Z_i) \quad [22]$$

Unlike the fairness gap, which has different equation specifications for the absolute or the relative case of inequality measurement, direct unfairness is specified as in equation 21 (or 22 for our empirical purposes) for both the relative and absolute case. This may consist of a computational reason to prefer direct unfairness over the fairness gap. Both multivariate methods clearly relate to the standardisation processes described previously in this thesis, such relationship is examined further in the next section.

2.5.4 Multivariate methods and standardisation

From the description of the mechanisms of standardisation and the multivariate methods, one can draw some comparisons. First, let us focus on direct unfairness and direct standardisation. If we recall, equation 7 specified an additively separable health function that was only a function of income and age. It is not difficult to see, that this equation is a simple linear form of equation 17, applied to the health case (and not health care). In any case, the general health function could be defined as:

$$h_i = h\ (N_i, P_{i,} SES_i, Z_i) \quad [23]$$

where N are need variables such as age and sex, P are lifestyle preferences, SES are measures of socio-economic status, commonly income and Z are other variables considered unfair. Following equation 23, the directly standardised health function could be obtained using a convenient regression and would be given by:

$$h_{i\_direct} = h_{i\_predicted}\ (N_{ref},\ P_{ref}, SES_i, Z_i) \quad [24]$$

Equation 24 is the exact equivalent for health of equation 223, which deals with health care. Therefore, the individual measure of direct unfairness is equal to the individual directly standardised measure of health.

In order to implement the measures of direct unfairness and the fairness gap, Fleurbaey and Schokkaert suggest the use of the (absolute) Lorenz curve apparatus (Fleurbaey and Schokkaert, 2009), although for the case of direct unfairness the relative Lorenz curve can be applied without altering the equation specification. For the relative case, the Gini Index suggested by the authors would be:

$$G_{du} = \frac{2\,Cov\,(h_{i\_du}, F(h_{i\_du}))}{\mu_{h\_du}} \qquad [25]$$

Alternatively, if one chooses to follow a concentration index approach, and uses direct unfairness as a ranking variable (as proposed by the Health Care Advantage approach, which will be the focus of Chapter 4), the directly standardised concentration index is given by:

$$CI_{direct} = \frac{2\,Cov\,(h_{i\_direct}, F(h_{i\_du}))}{\mu_h} \qquad [26]$$

Given the equivalence, between the individual measure of direct unfairness and the individual directly standardised measure of health, it holds true that $h_{i\_du} = h_{i\_direct}$. Thus, some rearranging of equation 26 is possible:

$$CI_{direct} = \frac{2\,Cov\,(h_{i\_du}, F(h_{i\_du}))}{\mu_h} \text{ x } \frac{\mu_{h\_du}}{\mu_{h\_du}} \qquad [27]$$

$$CI_{direct} = \frac{2\,Cov\,(h_{i\_du}, F(h_{i\_du}))}{\mu_{h\_du}} \text{ x } \frac{\mu_{h\_du}}{\mu_h}$$

$$CI_{direct} = \frac{\mu_{h\_du}}{\mu_h} \text{ x } G_{du} \qquad [28]$$

Thus CI_{direct} and G_{du} are only equal if the means of direct unfairness and observed health (μ_{h_du} and μ_h respectively) are equal. This could be the case in linear models with no interactions where the reference values for direct unfairness variables are set at the mean level of the population, but not necessarily so in non-linear specifications or where interactions exist.

Turning our attention to the fairness gap, a similarity with indirect standardisation exists, although it is less straightforward, as the relationship depends on whether the fairness gap (ratio) has been specified as a gap (absolute terms) or a ratio (relative terms). Following equation 12, a convenient regression allows us to estimate:

$$h_{i\_indirect} = h_i - h_{i\_predicted}\,(N_i,\ P_i, SES_{ref}, Z_{ref}) + \mu_h \qquad [29]$$

This is similar, although not exactly equal to the absolute definition of the fairness gap (equation 19). Nonetheless, given that μ_h is constant, both specifications of equations 19 and 29 would produce the same value for absolute inequality measures. If one considers that indirect standardisation is used in measures of relative inequality, then the appropriate comparison would be between equation 29 and equation 20. As we can see, both equations possess similarities, as they use the same convenient regression to predict health, but cannot be considered mathematical identities.

2.6 Legitimate vs. Illegitimate: where to draw the line

As mentioned earlier in the chapter, in general, researchers and policy makers may consider any variable over which an individual has no control a source of unfair inequality. However, the line between legitimate and illegitimate sources of inequality is not always so straightforward. So examples may be enlightening.

Lets consider the variable age. It is obvious that no one has any control over the aging process and, in health care, it is expected that young infants and older people have a greater need for care. Especially in the case of the elderly, it is far from debatable that their health status is, on average, poorer than the ones of their young fellows. Thus, hardly any one would consider placing the variable age in the effort category.

If we all agree that age is a circumstance, we must all admit that it is a source of unfair inequality. However, pure logic would tell us that if we are all subject to aging, we could all expect our health status to deteriorate over time. So, how much is aging really an illegitimate source of inequality? Some may consider it legitimate, as it simply means that the greater the age, the greater the need for health services. This explains why in general for healthcare delivery, age is considered a fair source of inequality.

Another interesting variable is smoking. The act of smoking is a choice the individual makes, and therefore, something he or she should be held responsible for. The placement of the smoking variables amongst effort variables is a common practice within researchers. As an effort variable, smoking is considered a legitimate source of inequality, as it is only fair that someone who smokes has a higher probability of falling ill.

Notwithstanding, in economic research we have enough evidence that shows that the smoking habit is one highly influenced by parental decision, over which an individual has no control (Balia and Jones, 2011, Jusot et al., 2013, Rosa Dias, 2009). Not only that, descriptive statistics also show that a high proportion of smokers start the habit at the early ages of adolescence, a time in which as non-adults they cannot be legally held responsible for many of their actions.

In a nutshell, whether a variable is considered legitimate or illegitimate is a normative decision that falls in the researcher's hands. As in any modelling, the aim is to be as close to the reality as possible. But the perception of the reality may vary in accordance to political, sociological and economic interests. Interestingly enough, the multivariate methods here described allow for different ethical positions, and, thus, different normative decisions regarding the placement of variables that can be considered fair or unfair sources of inequality.

Chapter 3: Empirical evidence of inequality in healthcare: international perspectives

3.1 Introduction

Over the past 20 years, several studies have applied the methods described previously to measure inequalities in health, health care utilisation and health care financing. In the following sections, we will highlight the most recent relevant studies of inequalities in health care utilisation, as this will constitute some ground for comparisons and conclusions afterwards, when the empirical analysis of possible inequalities in health care use in Brazil is performed.

The chapter in organised in four sub-sections. The first presents studies of high-income countries, where traditionally richer data is available and where this kind of study was first produced. A second section devotes itself to describing studies on Latin America, which constitute a benchmark for the analysis of Brazil. Due to its magnitude population wise, Brazil tends to present results that do not differ much from the average in Latin America. This is a result of the fact that the mean in Latin America is strongly influenced by the Brazilian results. A third part of this chapter reviews selected inequality studies performed in Brazil. Finally, the last section looks into evidence of inequality in the use of mammography and cervical screening, which is the specific topic of chapters 5 and 6.

3.2 High-Income countries – OECD and European Studies

In this section, we focus on three major international studies, each of which are landmarks in the field, and present their findings in some detail. Whereas two focus on OECD countries and were conducted by the OECD Health Equity Research Group, one uses European panel data to measure horizontal inequality in health care. They are presented chronologically by date of publication.

In general, the results of equity studies in high-income countries corroborate that pro-rich inequality in specialist visits exists, while pro-poor inequality in GP visits can be observed in most nations. The magnitude of inequality varies from setting to setting, and certain features of the health care system appear to influence the size of the inequality measure (Van Doorslaer and Koolman, 2000, van Doorslaer et al., 2000, Van Doorslaer and Masseria, 2004, d'Uva et al., 2009, Devaux and De Looper, 2012).

The review of equity studies in high-income countries may provide some insight to the Brazilian analysis. They can be considered as a basis for comparison and contrast, when taking into account specificities of particular health systems. For example, the UK has a universal tax-based health system, free at the point of consumption, and the measures of socio-economic inequality in health care in the region are relatively low, compared to other European or OECD nations (Van Doorslaer and Masseria, 2004, Devaux and De Looper, 2012). Brazil, in turn, also has a universal tax-based health system, free at point of consumption, albeit supplemented by private health insurance, which is both out-of-pocket purchased or employment-based. Another example refers to the relationship between mode of financing and health care utilisation. Evidence in high-income countries shows that private health insurance does increase utilisation in those countries, and that inequality is in general smaller in nations with a higher degree of public health expenditure (Devaux and De Looper, 2012). This relates directly to the Brazilian reality, and our results will also show that health insurance coverage is a predictor of greater use of care, and that this variable alone is the greatest contributor to overall unfair inequality.

3.2.1 Income-related inequality in use of medical care in 21 OECD countries *by Eddy van Doorslaer and Cristina Masseria (2004)*

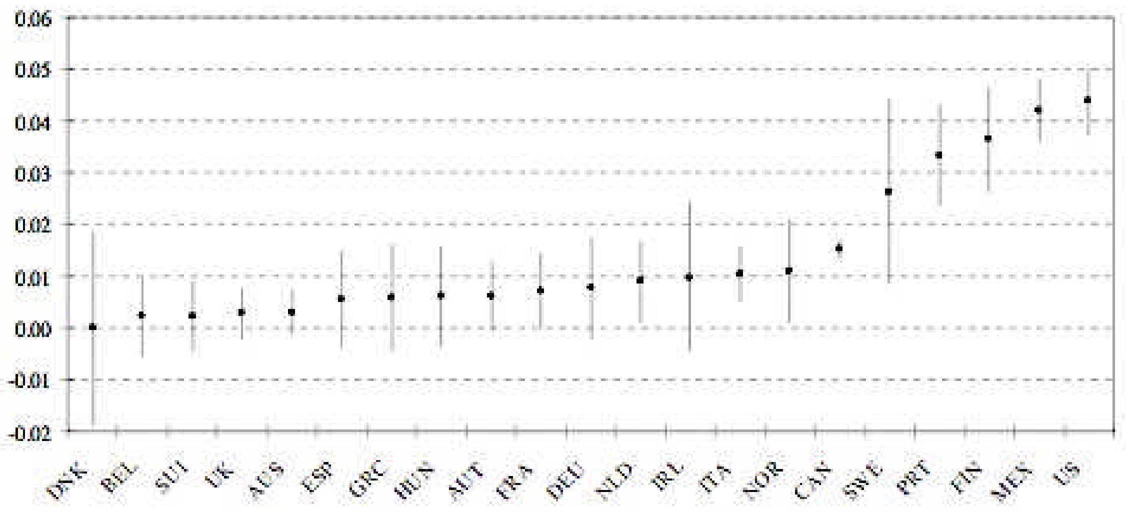
This study consists of the analysis of three outcome variables: physician utilisation, inpatient care and dentist visits in 21 OECD countries, namely Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Mexico, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States. Whenever possible the researchers have used data from the European Community Household Panel (held in year 2000). Even though several datasets were used for the non-European countries, the authors ensured that all were "nationally representative for the non-institutionalized adult population (i.e. individuals over the age of 16)" (Van Doorslaer and Masseria, 2004) and that the data was retrieved in the year 2000 or more recent, with the exception of the US, for which the data refers to 1999. The analysis drew upon quintile group distributions and concentration indices to analyse income-related horizontal inequity in health care utilisation.

The findings for physician utilisation differ when the categories GP or medical specialists are analysed separately. Whereas the study finds nearly no evidence of horizontal inequity in the distribution of GP visits across income groups[6], the distribution for consultation with a medical specialists often yield a positive concentration index, thus, confirming the existence of pro-rich inequality. Such inequality is found both for the number of visits and its probability, which means that not only are the better off more likely to visit a specialist, but also they visit more often.

[6] Where horizontal inequity in GP use exists, it is often negative in magnitude, indicating a pro-poor bias. The study found that after standardization for need, 10 countries have a statistically significant but small pro-poor inequality measure.

At an aggregate level, that is, when the variables GP visits and specialist visits are added up to produce a general physician utilisation vector, significant pro-rich horizontal inequality is found in about half of the countries. Figure 3.1 plots the indices for number of total visits, by country, with its respective 95% confidence interval. As one can see in the chart, the US, Mexico, Finland and Portugal, i.e. the countries on the right hand side of the chart, have a high degree of inequality.

Figure 3.1 – Inequality Indices for physician utilisation



Source: Van Doorslaer and Masseria, 2004, for OECD.

The analysis of inpatient care is less straightforward. Two explanatory variables were taken into consideration in this case: probability of admission into a hospital and number of nights spent in hospital. The authors point out that the use of the latter variable is rather problematic as so few as 10% of adults are admitted to hospitalisation and some end up staying for a very long time. This results in a lack of statistical power and wide 95% confidence intervals for the inequality indices.

Nonetheless, three groups of countries were identified in this category: a) countries with no evidence of inequality in inpatient care, like Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Spain, Sweden and the UK – in which the results might have been derived from the small samples sizes; ii) countries with an important pro-rich inequality, like Mexico and Portugal; and iii) countries with evidence of pro-poor inequality, such as Australia, Canada, Switzerland and the US. No EU member countries can be found in the latter two categories. Finally, the study shows that in all nations analysed a pro-rich inequality in both probability of use and frequency can be found with regards to the variable dentist visits.

Most if not all the countries involved in the analysis have a well-established health care system, which means that the found inequalities cannot be attributed to the lack of an institutional framework or newly developed institutions (Van Doorslaer and Masseria, 2004).

3.2.2 Measurement of horizontal inequity in health care utilisation using European panel data *by D'Uva, Jones and van Doorslaer (2009)*

This study analyses horizontal inequality for ten EU-members (Austria, Belgium, Denmark, Finland, Greece, Ireland, Italy, Netherlands, Portugal and Spain) using eight annual waves of the European Community Household Panel (ECHP).

The authors have chosen to calculate all measures of inequality in what they define as a "conventional" and "conservative" approach. In the conventional approach, the horizontal inequity index is given by the difference between the observed (unstandardized) concentration index (CI) and the need-predicted one ($CI_{need\text{-}predicted}$). Mathematically, we have:

$$HI_{conventional} = CI - CI_{need\text{-}predict} \qquad [1]$$

This is equivalent to indirect standardisation, as described in Chapter 2 and defined in equation 14 of that Chapter. The authors also estimate the non-need predicted health care utilisation function to calculate the "conservative" horizontal inequity index. In this case:

$$HI_{conservative} = CI_{non\text{-}need\text{-}predict} \qquad [2]$$

This method of standardisation has also been described in some detail in Chapter 2, it corresponds to direct standardisation, where the directly standardised healthcare function is estimated (as in equation 8 of Chapter 2) and the concentration index of the resulting distribution is calculated (equation 9 in Chapter 2). Thus, Bago d'Uva et al. (2009) consider direct standardisation a conservative approach to measuring income-related inequality.

Finally, D'Uva, Jones and van Doorslaer also made the distinction between short-run and long-run inequality. Due to the fact that they were dealing with longitudinal data, they were capable of obtaining short-run indices, for each wave, which later were weighted to compose the average short-run index. By contrast, the long-run indices were based on all waves available.

In here, as in the other study described, the analysis was separated between GP visits and Specialist visits, also known as primary and secondary care, respectively, in the literature, but no overall index was constructed. The results can be found in Tables 1 (a) and (b). For GP visits, two groups of countries emerge. Austria, Portugal and Finland present a positive index, indicating pro-rich inequality[7], all other countries display pro-poor inequality.

Regarding differences in the short and long-run, it can be said that there is mixed evidence

[7] As it can be apprehended from table 3.1 (a), Austria has a negative non-significant index for the long-run estimate of the conventional HI. In all other cases, it presents positive indices.

in the case of the conventional HI. Four of the ten countries present a small, i.e. more negative, index in the long-run, namely Ireland, Belgium, Greece and Austria. As to the conservative HI, only two nations reproduce this behaviour, Italy and Greece. From Table 3.1 (a), it can also be seen that, generally, the "conventional" is smaller than the "conservative" version, which the authors interpret as a confirmation of the assumptions regarding the contribution from need/non-need variables to inequality.

The results with regards to specialist visits are more consistent throughout the countries analysed. All nations have positive indices in either approach, demonstrating an unequivocal pro-rich inequality in secondary care. In this case, like in the case of GP visits, the conservative approach yields larger estimates, but in this case it "indicates that the differences between the two represents pro-poor contributions to inequity. If it is the case that the residuals are pro-poor and that they capture mainly justifiable variation in the use of specialists, then the "conventional" approach underestimates inequity in specialist use in most countries" (d'Uva et al., 2009).

Table 3.1 – (a) Conventional and Conservative Horizontal Inequality Index for GP visits

	"Conventional" HI						"Conservative" HI						"Conservative" HI – "Conventional" HI			
	AvgSR		LR		LR-AvgSR		AvgSR		LR		LR-AvgSR		Avg SR		LR	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Spain	–0.039*	(0.001)	–0.038*	(0.001)	0.001*	(0.0001)	–0.039*	(0.004)	–0.038*	(0.004)	0.001	(0.001)	0.000	(0.004)	0.000	(0.004)
Ireland	–0.045*	(0.002)	–0.054*	(0.002)	–0.010*	(0.0003)	–0.036*	(0.007)	–0.035*	(0.008)	0.001	(0.002)	0.009	(0.006)	0.019*	(0.008)
Italy	–0.027*	(0.001)	–0.024*	(0.001)	0.003*	(0.0001)	–0.031*	(0.003)	–0.033*	(0.003)	–0.002*	(0.001)	–0.004	(0.003)	–0.009*	(0.003)
Belgium	–0.053*	(0.002)	–0.055*	(0.002)	–0.002*	(0.0003)	–0.035*	(0.005)	–0.033*	(0.006)	0.002	(0.001)	0.018*	(0.004)	0.022*	(0.005)
Greece	–0.016*	(0.002)	–0.025*	(0.002)	–0.009*	(0.0002)	–0.019*	(0.005)	–0.021*	(0.005)	–0.002†	(0.001)	–0.003	(0.005)	0.004	(0.005)
Denmark	–0.020*	(0.004)	–0.016*	(0.004)	0.004*	(0.0004)	–0.016*	(0.007)	–0.014†	(0.008)	0.002	(0.002)	0.004	(0.006)	0.002	(0.007)
Netherlands	–0.028*	(0.001)	–0.022*	(0.001)	0.006*	(0.0002)	–0.015*	(0.004)	–0.013*	(0.005)	0.002	(0.001)	0.013*	(0.004)	0.009†	(0.005)
Austria	0.009*	(0.002)	–0.001	(0.002)	–0.010*	(0.0001)	0.010†	(0.005)	0.011†	(0.006)	0.001	(0.001)	0.001	(0.005)	0.012*	(0.006)
Portugal	0.018*	(0.001)	0.019*	(0.001)	0.001*	(0.0002)	0.022*	(0.004)	0.024*	(0.005)	0.002*	(0.001)	0.004	(0.004)	0.004	(0.004)
Finland	0.028*	(0.003)	0.028*	(0.003)	0.000	(0.0004)	0.033*	(0.006)	0.035*	(0.006)	0.002*	(0.001)	0.005	(0.005)	0.008	(0.006)

* Significant at 5%, assuming normality.
† Significant at 10%, assuming normality.

(b) Conventional and Conservative Horizontal Inequality Index for specialist visits

	"Conventional" HI						"Conservative" HI						"Conservative" HI – "Conventional" HI			
	AvgSR		LR		LR-AvgSR		AvgSR		LR		LR-AvgSR		AvgSR		LR	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Netherlands	0.026*	(0.002)	0.050*	(0.002)	0.024*	(0.0003)	0.037*	(0.007)	0.047*	(0.008)	0.010*	(0.001)	0.011†	(0.007)	–0.003	(0.008)
Belgium	0.034*	(0.003)	0.040*	(0.003)	0.007*	(0.0004)	0.052*	(0.007)	0.066*	(0.008)	0.014*	(0.002)	0.018*	(0.006)	0.025*	(0.007)
Denmark	0.052*	(0.008)	0.088*	(0.008)	0.035*	(0.0007)	0.057*	(0.013)	0.078*	(0.014)	0.021*	(0.004)	0.005	(0.011)	–0.009	(0.012)
Austria	0.090*	(0.003)	0.089*	(0.003)	–0.002*	(0.0002)	0.082*	(0.006)	0.088*	(0.006)	0.007*	(0.001)	–0.009†	(0.005)	0.000	(0.006)
Spain	0.083*	(0.001)	0.089*	(0.001)	0.005*	(0.0001)	0.092*	(0.005)	0.105*	(0.006)	0.013*	(0.001)	0.009†	(0.005)	0.017*	(0.006)
Greece	0.073*	(0.002)	0.070*	(0.002)	–0.003*	(0.0003)	0.100*	(0.007)	0.106*	(0.007)	0.006*	(0.001)	0.027*	(0.006)	0.036*	(0.007)
Italy	0.096*	(0.001)	0.094*	(0.001)	–0.001*	(0.0001)	0.103*	(0.004)	0.114*	(0.005)	0.012*	(0.001)	0.007†	(0.004)	0.020*	(0.005)
Finland	0.134*	(0.004)	0.143*	(0.004)	0.009*	(0.0007)	0.142*	(0.008)	0.152*	(0.009)	0.009*	(0.001)	0.009	(0.008)	0.009	(0.008)
Ireland	0.123*	(0.004)	0.128*	(0.004)	0.006*	(0.0007)	0.142*	(0.012)	0.157*	(0.013)	0.015*	(0.002)	0.019†	(0.010)	0.028*	(0.011)
Portugal	0.199*	(0.002)	0.204*	(0.003)	0.005*	(0.0005)	0.180*	(0.006)	0.195*	(0.006)	0.015*	(0.001)	–0.019*	(0.006)	–0.009	(0.006)

* Significant at 5%, assuming normality.
† Significant at 10%, assuming normality.

3.2.3 Income-related inequality in health services utilisation in 19 OECD countries *by Marion Devaux and Michael de Looper (2012)*

This study constitutes an update and extension of the 2004 study by van Doorslaer et al. The analysis for GP, specialist visits and overall (outpatient) use of health services is brought forward from the early 2000s to 2008/09. It also adds a new variable to the analysis, cancer screening. Finally, it presents an interesting cross country correlation analysis of how inequalities in health care use are related to health care financing.

The study obtains the following results:

a) For doctor visits (GPs + specialists), most countries present a small pro-rich inequality, with the exception of the US, where a higher level of inequality is found. When frequency of visits is analysed the pattern is less clear. It is noticeable, however, that in Finland, Poland, the US and Spain a high-level of pro-rich inequality is found, indicating that the better off use health services more often than their poorer counterparts.
b) When GP visits are considered on their own, three patterns of behaviour are distinguishable. In Czech Republic, Spain, Switzerland, Ireland, Austria, Belgium, United Kingdom, Hungary and Slovenia (9 countries), no evidence of inequality in the probability of seeing a GP is found. Estonia, Canada, Finland, Poland, New Zealand, the Slovak Republic, and France display a small but statistically significant pro-rich inequality and only Denmark shows the opposite pattern, that is, significant pro-poor inequity. With respect to number of visits, the behaviour is different. Whereas most of the countries do not present any inequity in that aspect, Denmark, Belgium, Austria, France, New Zealand, and Canada display pro-poor inequality, which is equivalent of saying that, for a given level of need, the poor visit the GP more often than the rich.
c) The results obtained for specialists are far more consistent. In all countries, the well-off are, in general, more likely to visit a specialist and do so more often. Nonetheless, taking into account 95% confidence intervals, the measured inequality is not statistically significant in the UK, Czech Republic and Slovenia, with respect to the probability of visits; and Slovenia, Czech Republic, Denmark, New Zealand, Slovak Republic and Belgium, for frequency of visits.
d) The results for dentist visits is consistent with the ones found in a recent study of the over 50 population in Europe (Listl, 2011) and demonstrates a clear pro-rich inequality of probability of dentist visit in all 19 countries. The pattern for frequency of visits is similar to that of probability, with the remark that for Czech Republic, Switzerland and Slovenia no statistical significance can be inferred.
e) Extending the previous study, the authors found pro-rich inequality in breast cancer screening for almost all countries involved in the study. This inequality was significant in

only eight: Belgium, Canada, Estonia, France, Ireland, New Zealand, Poland, and the United States. Devaux and de Looper also made an attempt to find a relationship between cancer screening and the health system features (e.g. nation-wide population based programmes), but no clear relationship could be established.

f) Finally, the authors compared health care utilisation against three categories of financing: public health setting, out-of-pocket payments and private health insurance. For each category, scatter plots were built as a way to determine the relationship between the financing source and the observed use. The conclusions were that certain system features have an important impact on equity. In the authors' own words:

> "Broader health insurance coverage improves access. The higher the share of public health expenditure, the lower the inequity in doctor visits. Similarly, greater inequity in specialist visits accompanies a higher degree of private provision. A greater share of out-of-pocket payments is associated with inequity in specialist and dental care. Secondary private health insurance facilitates the use of care, with the privately insured more likely to visit doctors and dentists." (Devaux and De Looper, 2012).

3.3 Evidence on Latin America

We now turn our attention to Latin America, the region in which Brazil finds itself. Unlike the OECD, Latin America is composed of a few middle-income countries and several low-income ones – and indeed, since 2013, Chile has been classified by the World Bank as a high-income country. Furthermore, health systems of any kind have not been long established in the region, which can be problematic when evaluating inequalities. As a more detailed section on Brazil-specific studies will follow, I have selected two major cross-country studies focusing on making equity comparisons within the region as a whole. The first evaluates inequalities and inequities in health, health care use and financing in 6 countries, Brazil, Ecuador, Guatemala, Jamaica, Mexico and Peru. Only measures of inequality in utilisation will be reviewed, as they are the ones of interest to our purposes. The second study analyses the access to health care in four large cities in South America. Although it is not nationally based, it is highly cited in the literature and the size of the cities in terms of population justifies substantial policy interest. As before, a chronological order of presentation is followed.

In a nutshell, equity studies in Latin America demonstrate that pro-rich inequality exists for several forms of health care utilisation. The comparison with high-income countries is not always possible, as in general Latin American studies focus on physician visits, which do not differentiate between GPs and specialists. Nevertheless, evidence points to the fact that inequality in preventive care is in general larger when compared to curative care, of which physician visits in the most common form (Rossi et al., 2009, Suárez-Berenguela, 2000).

3.3.1 Health System Inequalities and Inequities in Latin America and the Caribbean: Findings and Policy Implications *by Rubén M. Suárez-Berenguela (2000)*

Effectively Suárez-Berenguela has produced a report of several studies carried out in the auspices of the World Bank and Pan-American Health Organization. In the late 1990s, the two multilateral organizations joined forces to fund a project that informally received the name of EquiLAC[8], in which equity in Latin America and the Caribbean was analysed. Due to scarcity of resources, only six nations (Brazil, Ecuador, Guatemala, Jamaica, Mexico and Peru) were effectively studied, but together they correspond to more than 67% of the total population, of the gross domestic profit (GDP) and the health expenditure in the region. The importance of this project should not be neglected, as it was the first systematic attempt to measure inequality and inequity in health and health care in Latin America and the Caribbean.

Even though all the countries applied the same methods (previously defined by the World Bank and PAHO), not all countries have managed to produce comparable results, due to the lack of availability of data or inconsistency amongst the different datasets. With regards to measures of inequality in health care, Guatemala did not have sufficient data to perform the analysis. In the other countries, only in Mexico was inpatient care evaluated and only Brazil had data on long-lasting illnesses available. Table 3.2[9] presents the results obtained for inequality in health care use.

Table 3.2 – Inequality in Health Care utilisation, by category

Countries/Variables	CI observed	CI need-predicted	HI
Curative Care			
Brazil	0.056	0.040	0.097
Ecuador	0.077	0.009	0.068
Jamaica	0.167	-0.003	0.170
Mexico	0.082	-0.004	0.086
Peru	0.167	-0.056	0.111
Chronic Care			
Brazil	0.119	0.054	0.065
Hospitalization			
Mexico	0.130	-0.005	0.099
Preventive Care			
Brazil	0.194	0.012	0.182
Ecuador	0.116	0.010	0.107
Mexico	0.122	0.023	0.125

Source: Suárez-Berenguela, 2000. Headings changed by the author.

[8] The EquiLAC Project is analogous to ECuity Project in Europe, lead since the early 1990s by Eddy van Doorlaer and Andrew Jones.
[9] Table 3.2 appears to have some inconsistencies. Brazil and Peru appear to have a problem in the sign of the reported need-predicted CI. The problem in the case of Mexico goes beyond sign. The table explicitly reproduces the values reported by the original authors.

As we can see in the last column of the table, all countries present a positive health inequality index, indicating pro-rich inequality. It is worth highlighting that inequalities in curative care appear to be smaller than in preventive care, which is understandable in countries with lower income. Also, in the case of Brazil, the measure for chronic care is the smallest of them all, indicating a lower level of pro-rich inequality for the treatment of long-standing illnesses.

3.3.2 Horizontal Inequity in access to health care in four South American cities *by Rossi, Balsa and Triunfo (2009)*

This study acknowledges the fact that, in Latin America, all too often measures of inequality cannot be compared between countries (or regions) due to data incompatibility. To enable comparisons, the authors restrict the regions and select four major cities in four different Latin America countries (Buenos Aires, Mexico DF, Montevideo and São Paulo), all included in the same survey, for which, thus, comparisons can be made. The survey used is Survey on Health, Wellbeing, and Aging (Encuesta de Salud, Bienestar, y Envejecimiento, SABE), which took place in 1999/2000, and included seven cities in Latin America and the Caribbean: Bridgetown (Barbados), Buenos Aires (Argentina), La Habana (Cuba), Mexico DF (Mexico), Montevideo (Uruguay), Santiago de Chile (Chile), and São Paulo (Brazil).

Table 3.3 presents the horizontal inequality index for each city in all categories researched. From the table, one may see that in general a pro-rich inequality of physician visit exists, although the magnitude varies with time and for each city. These results should be considered parsimoniously, given that statistical significance is only observed in Montevideo (12 months and 4 months) and Santiago (4 months). The analysis of inpatient care is less obvious, particularly as statistical significance is not achieved in any site. In terms of direction, whereas Buenos Aires and São Paulo display a positive value, indicating pro-rich inequality; Santiago and Montevideo yield negative values, displaying pro-poor inequality. Particularly the case of Santiago is noticeable, as the pro-poor inequality is fairly large in magnitude, although as we said before, not statistically significant (Rossi et al., 2009)..

When preventive services were analyzed, all four regions presented significant pro-rich inequality in all categories, namely prostate exam, cervical screening (informally known as pap test), mammogram and breast exam. It is interesting to see that in three of the four cities, the inequalities are larger for prostate exams than for the other procedures, which might indicate that men are more affected by the pro-rich inequality in preventive care. Naturally, to be certain of this assertion, further investigation is needed. Furthermore, the values observed in preventive care are mostly larger than the ones found in curative care, which is consistent with the findings in the EquiLAC study. The values for mammography screening and cervical screening are of interest as an empirical application using those two outcome variables is to follow. Comparability, however, is difficult because the only city analyzed by Rossi, Balsa and Triunfo in Brazil is São Paulo, the wealthiest and best-equipped city of the country.

Finally, the evidence with regards to the quality of care is less straightforward. Pro-rich inequality is found when the measure is time to get to the appointment, indicating that poor people are more subject to waiting lists. When the indicator is time in waiting room, the results are also positive, indicating that the better-off wait less time to be seen by a health care professional than their worse-off counterparts. The inequality is pro-poor for travel time to the appointment, although it is not always statistically significant when taking into account the standard errors. At last, the evidence is mixed for requested examination and medication prescribed. Two categories emerge. In Buenos Aires and Santiago, more examinations are requested for the poor and rich are prescribed more medication (pro-poor and pro-rich inequalities respectively). In São Paulo and Montevideo, the dynamics is inverse: more examinations are requested for the rich and the poor are prescribed more medication (pro-rich and pro-poor inequalities, respectively).

Table 3.3 – HI measures for each city, by form of care

	Buenos Aires, Argentina (1)	*Sao Paulo, Brazil* (2)	*Santiago, Chile* (3)	*Montevideo, Uruguay* (4)
MD Visits and Hospitalizations				
MD visit past 12 months	0.007	0.011	0.017	0.041**
	(0.008)	(0.007)	(0.010)	(0.009)
MD visit past 4 months	0.028	0.000	0.047**	0.036**
	(0.015)	(0.009)	(0.016)	(0.013)
Hospitalized past 4 months	0.093	0.138	-0.290	-0.003
	(0.096)	(0.071)	(0.161)	(0.074)
Quality of Care (last visit)				
Time to get appointment <7 days	0.011	0.047**	0.059**	-0.038**
	(0.019)	(0.016)	(0.019)	(0.007)
Time travelling to appointment <30 min	-0.029	-0.014	-0.036	-0.007
	(0.018)	(0.018)	(0.019)	(0.008)
Waiting time in office <30 min	0.088**	0.103**	0.086**	0.013
	(0.026)	(0.025)	(0.029)	(0.009)
Examinations requested	-0.010	0.059**	-0.022	0.002
	(0.022)	(0.013)	(0.022)	(0.025)
Medication prescribed	0.003	-0.002	0.022	-0.034*
	(0.023)	(0.015)	(0.012)	(0.016)
Use of Preventive Services (past 2 yrs)				
Prostate exam	0.122**	0.130**	0.117**	0.207**
	(0.038)	(0.028)	(0.041)	(0.035)
Pap test	0.108**	0.082**	0.039	0.166**
	(0.029)	(0.020)	(0.028)	(0.040)
Mammogram	0.174**	0.128**	0.097**	0.127**
	(0.033)	(0.024)	(0.035)	(0.034)
Breast exam	0.097**	0.095**	0.013	0.047*
	(0.024)	(0.019)	(0.022)	(0.023)

Bootstrapped standard errors in parentheses. Data: SABE 1999/2000.
* Statistically significant at $p<0.05$; ** statistically significant at $p<0.01$.

Source: Rossi, Balsa and Triunfo, 2009.

3.4 Evidence in Brazil

Brazil has historically struggled with the distribution of its own resources. With more than 50 million people living on less than two dollars a day (IBGE, 2015), poverty and inequality have been issues of interest for policy makers as well as academics for quite some time. However, whereas income inequality has been analysed in depth, health inequalities have gained far less attention and inequalities in health care even less so. The lack of empirical evidence in this area has been partly justified by the novelty of the health system. As it was instituted only in 1988, it was not in the political agenda to submit the system through more detailed analysis. Furthermore, because the system had been legalized and formalized from the top down, it has difficulties in its operationalization and funding. These two topics have been of greater academic concern for researchers within the nation (Marques and Mendes, 2010).

Nonetheless, there have been a few contributions to this literature in the years since 2000. All in all, the studies find unequivocal evidence of pro-rich inequalities in health and access or utilization of health care, and some evidence of inequalities related to educational attainment and employment (Campino et al., 2001, Giatti and Barreto, 2006, Macinko and Lima-Costa, 2012, Almeida et al., 2013). There is also evidence of higher inequalities amongst women, the elderly and dark-skinned (black or mixed race) (Neri and Soares, 2002, Pellegrini Filho, 2004).

The following section presents the five most relevant systematic analyses of inequalities in the Brazilian health care system. These studies have been chosen to be reviewed in more detail as researchers that specialize in Brazil often cite them when referring to inequality studies. The study by Coelho Campino et al (2001) was the first to attempt at a national level analysis, although the data source used did not adequately cover all regions of the country. The study on inequalities in healthcare financing (2007) makes use of data from the National Family Budget Survey, which consists of a large sample of households and is representative at national and subnational levels, hence its relevance. Finally, the last two studies to be presented here use the most reliable source of data on health care utilization in Brazil until the time of publication, the Health Supplement of the National Household Sample Survey (PNAD).

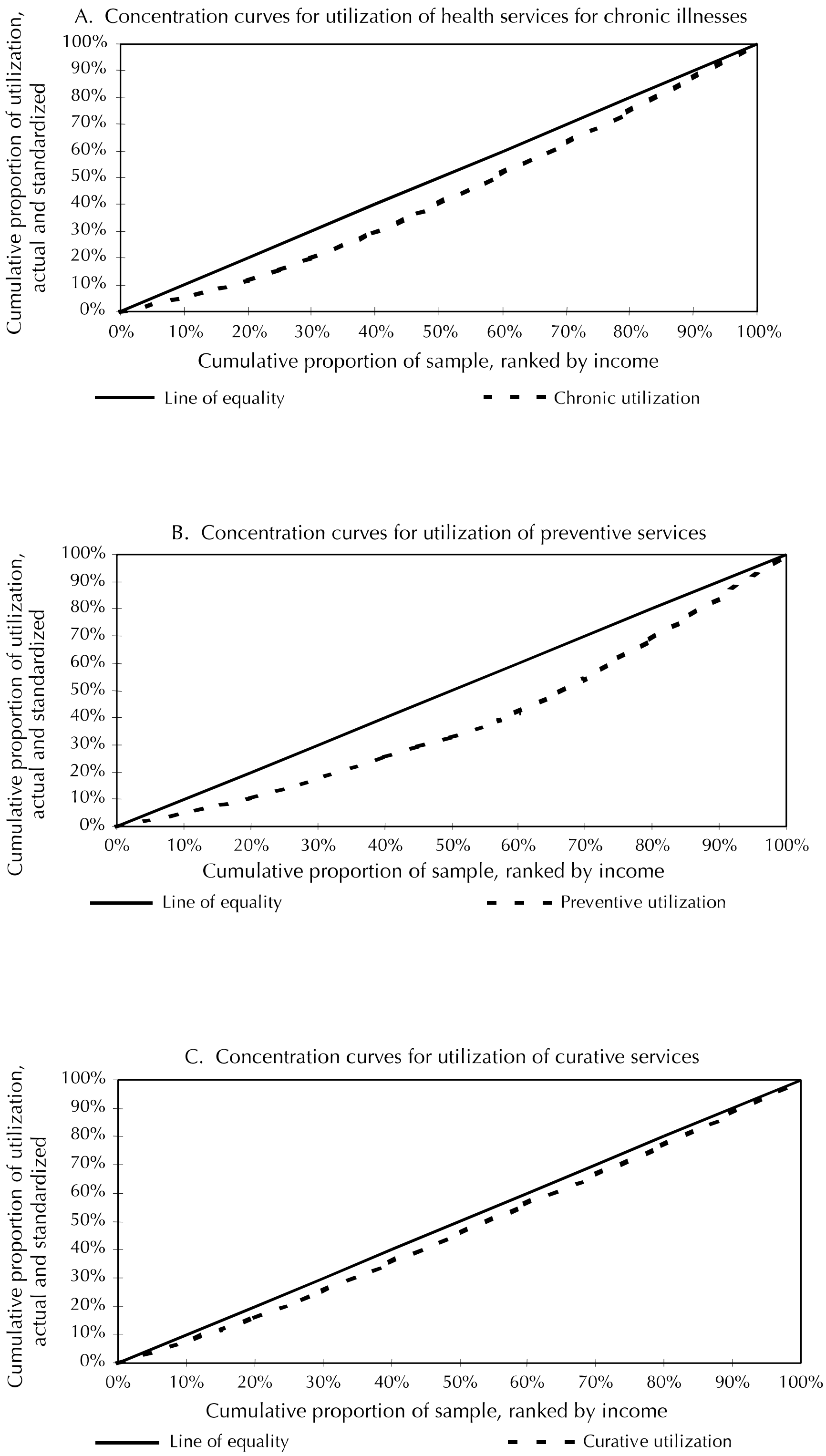
3.4.1 Health System inequalities and poverty in Brazil (WB/PAHO) *by Campino, Diaz, Paulani, de Oliveira, Piola and Nunes (2001)*

This study was performed in the realm of the EquiLAC project, already mentioned in Chapter 2. Even though the study performed the measurement of inequalities in health outcome, financing and utilization in Brazil, for the purposes of this review only the results obtained for health care use will be described.

The data source consisted of the Life Standard Measurement Survey, conducted in 1997 by the National Institute of Geography and Statistics (IBGE), in which 19,049 individuals were asked about education, health, housing, employment, fertility, contraception, migration, and time use, among other areas. This was the only wave of this particular survey, as the institute decided to incorporate most of those questions in the recurrent national survey of households, divided by themes in its periodical supplements. Although the survey was extensive, it is not representative of the nation as not all regions have been covered.

The analysis of utilization of health services was divided in three categories: i) treatment of chronic health problems; ii) utilization of curative services and iii) preventive care. For the first category, an individual was considered to have a chronic illness if they had answered positively to having being diagnosed with one (or more) of the following conditions: hypertension and other heart related problems, diabetes, respiratory distress, digestive malfunctioning, gynaecological or prostate related problems, cancer, bone/muscular/joint problems, neuropsychiatric conditions and hypercholesterolemia. The categories curative care and preventive care are defined as complementary. If an individual had sought care and was effectively diagnosed and treated for a medical condition, he had received curative care. By opposition, if he had sought care but no medical problem was encountered, the care given, with all its procedures and offered services, was categorized as preventive (Campino et al., 2001).

Figure 3.2 – Concentration Curves for Utilization of Health Services in Brazil (1997)[10]



Source: Coelho Campino et al, 2001 for EquiLAC .

[10] Although the y-axis is labelled as actual and standardised utilisation, only the standardised curves are showed in the graphs. This is an inconsistency of the original publication.

Figure 3.2 above presents the concentration curves for each of the three analysed categories, already standardized for demographic and biological factors. It is clear that in all the categories a pro-rich inequality exists. Nevertheless, the inequality is smaller for curative care and has its largest value (given by twice the area between the two lines) in preventive care.

3.4.2 The individual's status in the labour market and health inequity in Brazil *by Luana Giatti and Sandhi Maria Barreto (2006)*

The goal of this study was to investigate the existence of inequalities in health and in the utilization of health care dependent on the individual's status in the labour market. The study used a sample of 39,925 males, aged between 15 and 64 and resident of 10 metropolitan regions in Brazil. The authors justified the selection of males only in light of the evidence of income inequality between males and females. By excluding the latter group, they aimed to observe the direct effect of labour market insertion and health outcome and health care and have explicitly neglected any gender related effect.

In terms of methods, Giatti and Barreto used a multinomial logistic regression to establish the relationship between labour market insertion and several health and health care indicators. For each variable of interest, the authors controlled for age, schooling, income, region and labour market insertion of the head of the house. Table 3.4 below presents the odds ratios for each category analysed. The reference category for calculation of the ratios was the formally employed.

As it can be seen, workers not encompassed in the formal market are more likely to report bad-health (the worst case being of individuals outside the labour market), to stay in bed due to illness and to report chronic conditions. As in the case of self-reported health, the indicators are worse for individuals outside the labour market. With regards to health care, the pattern is not as clear as some ratios are smaller than 1, indicating that the non-reference population uses the health care system less than their formally employed counterparts; but indicators sometimes are higher than 1, indicating the exact opposite. It is noteworthy, however, that the odds ratio for outside-the-labour-market individuals with regards to admission to hospital is very large (larger than two), from which one can conclude that people under this category are at least twice as likely to be admitted into hospitals than formal workers (Giatti and Barreto, 2006).

Table 3.4 – Odds ratios for health and health care use, according to labour market status

Variables	Informal labor Adjusted OR (95% CI)	Status in the labor market Unemployed Adjusted OR (95% CI)	Outside of the market Adjusted OR (95% CI)
Self-perception of health			
Good	1.00	1.00	1.00
Regular	1.28 (1.18-1.39)	1.26 (1.12-1.40)	1.27 (1.19-1.37)
Bad	1.24 (1.08-1.43)	1.88 (1.45-2.42)	2.01 (1.64-2.45)
Other informant	0.58 (0.50-0.61)	0.43 (0.41-0.45)	0.37 (0.25-0.39)
Time off usual activities during the last 15 days			
No	1.00	1.00	1.00
Yes	1.04 (0.93-1.17)	0.90(0.74-1.09)	2.05 (1.62-2.60)
Bedridden during the last 15 days			
No	1.00	1.00	1.00
Yes	1.36 (1.14-1.63)	1.34 (0.87-2.07)	2.83 (2.04-3.93)
Report of chronic diseases			
No	1.00	1.00	1.00
Yes	1.02 (0.93-1.11)	1.06 (0.95-1.17)	1.41 (1.22-1.63)
Private health insurance plan			
No	1.00	1.00	1.00
Yes	0.21 (0.18-0.24)	0.35 (0.30-0.40)	0.38 (0.33-0.44)
Medical consultation during the last 15 days*			
No	1.00	1.00	1.00
Yes	0.88 (0.80-0.98)	1.08 (0.78-1.50)	1.58 (1.34-1.86)
Number of medical consultations over the preceding year*			
None	1.00	1.00	1.00
1	0.82 (0.75-0.90)	0.95 (0.79-1.15)	0.81 (0.71-0.93)
2	0.81 (0.72-0.91)	0.99 (0.86-1.12)	0.95 (0.80-1.13)
3 or more	0.82 (0.75-0.90)	1.03 (0.83-1.28)	1.57 (1.36-1.79)
Number of admissions to hospital over the preceding year*			
None	1.00	1.00	1.00
1	1.09 (0.93-1.28)	1.02 (0.73-1.43)	2.04 (1.67-2.49)
2 or more	0.98 (0.66-1.46)	0.96 (0.62-1.49)	3.54 (2.27-5.52)

Notes: Reference category: formal labor; Adjusted OR (95% CI): Odds ratio with 95% confidence interval, adjusted for age, schooling, per capita household income, reference person in the household, region of residence, retired status and informant
*Adjusted for private health insurance plan, in addition to all the other factors cited.

Source: Giatti and Barreto, 2006.

3.4.3 An Analysis of equity in Brazilian health system financing *by Maria Alicia Uga and Isabela Santos (2007)*

This study consisted of an analysis of the financing aspect of inequality. Its main objective was to observe to what extent the notion of progressivity, in which the expenditure in healthcare is inversely related to income, was fulfilled in the system. In the analysis, the authors considered basically three sources of financing: i) government expenditures that finance the national health system; ii) out-of-pocket spending on health services plus health insurance premiums paid by households; and iii) corporate expenditures in health care, both through taxation, such as Corporate Income Tax, or IRPJ; Social Contribution on Net Profit, or CSLL; and COFINS and through the provision of complementary medical and hospital coverage to employees. In terms of the data used, they relied on the National Family Budget Survey (Pesquisa de Orçamentos Familiares – POF), conducted in 2002. Table 3.5 presents the composition of health financing, by income decile.

Table 3.5 – Income, composition and total health financing by income decile

	Per capita family income decile (from lowest to highest)									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Income (percent)[a]	1.00	1.92	2.74	3.56	4.53	5.80	7.59	10.43	16.34	46.10
SUS										
Total SUS										
Percent[a]	0.78	1.45	2.56	4.39	4.26	6.40	8.23	10.93	16.89	44.11
Fraction of income	3.42	3.28	4.06	5.34	4.08	4.78	4.70	4.54	4.48	4.15
Direct taxes (percent)[a]	0.67	1.23	2.36	4.36	3.98	6.29	8.13	10.86	17.05	45.08
Indirect taxes (percent)[a]	1.32	2.50	3.53	4.53	5.59	6.89	8.70	11.24	16.16	39.53
Private health insurance										
Percent[a]	0.28	0.32	0.78	1.22	2.77	3.15	5.09	11.42	19.94	55.03
Fraction of income	0.43	0.25	0.44	0.53	0.94	0.83	1.03	1.68	1.88	1.84
Out of pocket										
Total out-of-pocket										
Percent[a]	1.76	2.79	3.99	5.14	6.21	7.00	9.38	12.26	14.44	37.05
Fraction of income	6.76	5.58	5.59	5.52	5.26	4.62	4.74	4.50	3.39	3.08
Medicines (percent)[a]	2.59	3.66	5.16	6.62	7.51	8.24	10.55	13.28	14.55	27.84
Total private										
Percent[a]	1.33	2.08	3.07	4.01	5.23	5.89	8.16	12.02	16.01	42.20
Fraction of income	7.19	5.83	6.02	6.05	6.20	5.46	5.77	6.19	5.26	4.92
Total health financing										
Percent[a]	1.09	1.80	2.84	4.18	4.79	6.12	8.19	11.53	16.41	43.05
Fraction of income	10.61	9.11	10.08	11.39	10.28	10.24	10.48	10.73	9.75	9.07

[a] Percentage of total national income, taxes, or spending in each category accounted for by members of the income decile.

Source: Uga and Santos, 2007.

Although the authors conclude that in general the financing of health care in Brazil is neutral, as progressivity in public expenditure is compensated by regressivity of private payments, a few remarks about the results shown in the table above should be of interest. Firstly, the distribution of income indicates the strong inequality that exists with regards to this aspect. Secondly, out of pocket spending yields the most regressive distribution in all the analyzed categories. When looking at the components of out-of-pocket expenditure, the authors realized that purchase of drugs consisted of the main component, and that it absorbed 82.5% of the total spending for the poorest decile opposed to 42% of out-of-pocket spending for the richest 10% of the population. Finally, Uga and Santos acknowledge that measures of inequality in financing in the Brazilian Health System often disregard the fact that part of the population faced financial barriers (so the measure of inequality could be even greater) and that the regressivity of private spending might cause impoverishment (Ugá and Santos, 2007).

3.4.4 Horizontal equity in health care utilization in Brazil, 1998–2008 *by James Macinko and Maria Fernanda Lima-Costa (2012)*

The objective of this study is to measure income-related horizontal equity and observe its change over time for the period between 1998 and 2008, a period which the authors consider to be of major economic and social change (Macinko and Lima-Costa, 2012). The authors have used the traditional bivariate concentration-index type measures (Wagstaff et al., 1991b, Van Doorslaer et al., 1997a) already described in the previous chapter, and have calculated the measures of inequality for physician visits in the past 12 months, hospitalizations in the past 12 months, usual source of care, any use of healthcare services in the past 2 weeks and dental visits in the past 12 months.

In terms of data, they have used Health Supplement of the National Household Sample Survey (PNAD) for the years 1998, 2003 and 2008, which I will also use to perform my analysis. In total, those three samples add to more than 1.2 million individuals. The survey has a complex design and is representative at national and subnational levels.

To perform the analysis, the authors control for a range of variables, namely: age, sex, self-assessed health, prevalence of chronic conditions, schooling, region, urban/rural location, coverage by health insurance and log of family income. Particularly with regards to the prevalence of chronic conditions, there are 12 listed in the survey, although the authors only use 11 (arthritis, cancer, diabetes, asthma, hypertension, heart disease, kidney failure, depression, tuberculosis, cirrhosis, and tendinitis). They explicitly leave out back problems. As I will point out in the next chapter, although controlling for this conditions is in principle correct, the data appears to be biased in that wealthier population groups have a higher prevalence of these. Therefore, the measure of inequality produced by this study may be underestimated.

The choice of using family income in log terms as opposed to equivalised (family) income may also result in a smaller measure of inequality, given that family income does not adjust for family size when creating an income-rank. It is possible for a family to have larger (aggregate) family income than another, but be worse off. Imagine a family with four children and two income-achieving adults, as opposed to another family with one child and two adults with income. Even if the salaries of both adults in the small family are lower than that of their large family counterparts, it is perfectly possible for them to be better off in the income rank, as their income only has to stretch as far as the needs of three people. Thus, creating the income rank based on family income alone (not adjusting for family size) may be misleading and bias the calculated measure of inequality.

The results of the study are presented in Table 3.6 below. They show that inequality is pro-rich for physician visits, usual source of care, use of healthcare and dentists visits and is pro-poor for hospitalizations. The table also demonstrates that income-related inequality is decreasing for all outcome variables, and is much larger for dentist visits than for any other form of care. According to the authors, the magnitude of the inequality is small, although as said, their choice of covariates and of income variable may have biased the measures reported.

Table 3.6 – Concentration index and Horizontal inequity index by outcome measure

Variable	Unstandardized Concentration Index (CI)				Horizontal inequity index (HI)			
	1998	2003	2008	% change 1998 to 2008	1998	2003	2008	% change 1998 to 2008
Doctor visit (12 months)	0.0500 (0.0011)	0.0400 (0.0021)	0.0330 (0.0016)	−51.52	0.0642 (0.0011)	0.0444 (0.0021)	0.0357 (0.0018)	−79.83
Hospitalization (12 months)	−0.0810 (0.0043)	−0.0530 (0.0051)	−0.0430 (0.0051)	88.37	−0.0430 (0.0043)	−0.0263 (0.0049)	−0.0127 (0.0049)	238.58
Usual source of care	0.0290 (0.0010)	0.0070 (0.0025)	0.0040 (0.0021)	−625.00	0.0323 (0.0010)	0.0079 (0.0025)	0.0039 (0.0029)	−728.21
Any healthcare service-use (2 weeks)	0.0660 (0.0032)	0.0440 (0.0047)	0.0440 (0.0042)	−50.00	0.1019 (0.0032)	0.0651 (0.0047)	0.0648 (0.0045)	−57.25
Dental visit (12 months)	0.2180 (0.0019)	0.1780 (0.0032)	0.1390 (0.0028)	−56.83	0.2308 (0.0018)	0.1943 (0.0032)	0.1514 (0.0029)	−52.44

Numbers are concentration indices with standard errors in parentheses.
Values <0 indicate pro-poor and >0 indicate pro-rich utilization.
HI is the difference between actual healthcare use and predicted utilization based on health needs.
All values are statistically significantly different from previous periods ($p < 0.05$); except any healthcare service use for 2003 and 2008; and hospitalizations between 2003 and 2008.
Data source: Brazilian National Household Sample Survey (PNAD) 1998, 2003, 2008.

Source: Macinko and Lima-Costa, 2012.

3.4.5 Analysis of the evolution and determinants of income-related inequalities in the Brazilian health system, 1998–2008 by *Gisele Almeida, Flavia Mori Sarti, Fernando Fagundes Ferreira, Maria Dolores Montoya Diaz and Antonio Carlos Coelho Campino (2013)*

This final study is similar in nature to the one performed by Macinko and Lima-Costa. It also devotes itself to the evolution of income-related inequality in Brazil between 1998 and 2008. It does not only focus on healthcare outcomes, as it also measures inequality for self-assessed health, physical limitation and chronic conditions.

It also uses data from the Health Supplement of PNAD, but the choice of covariates is different. The author choose household income instead of family income, relying on the understanding that people living in the same household contribute to the wellbeing of other members of the house, regardless of familiar status. They also control for household size, which is a desired attribute. However, like Macinko and Lima-Costa, when measuring inequality in healthcare, they also control for chronic conditions (all 12), in spite of the unreasonable pattern of much higher prevalence amongst the richer quintiles. Thus, the calculated inequality in terms of health care could also be biased downwards. Other covariates include age, sex, self-assessed health, race, physical limitation, education, activity status, coverage by health insurance, urban/rural location, region and family type.

Also on chronic conditions, the authors hypothesize that the change in this measure of health went from pro-poor in 1998 to pro-rich in 2003 and 2008, is due to a change in the questionnaire. From 2003 onwards, respondents were asked whether they had been diagnosed with the condition, not if they had it (Almeida et al., 2013). Whereas this is a possible scenario, using such variables as controls for measuring inequality in healthcare is still problematic, as there are no legitimate reasons by which richer individuals are more prone to developing the chronic conditions observed (arthritis, cancer, diabetes, asthma, hypertension, heart disease, kidney failure, depression, tuberculosis, cirrhosis, back problems and tendinitis). Hence, they do not translate a measure of healthcare need. Table 3.7 shows the results produced by the authors.

Table 3.7 – Concentration and Horizontal Equity indices for health status and health care use

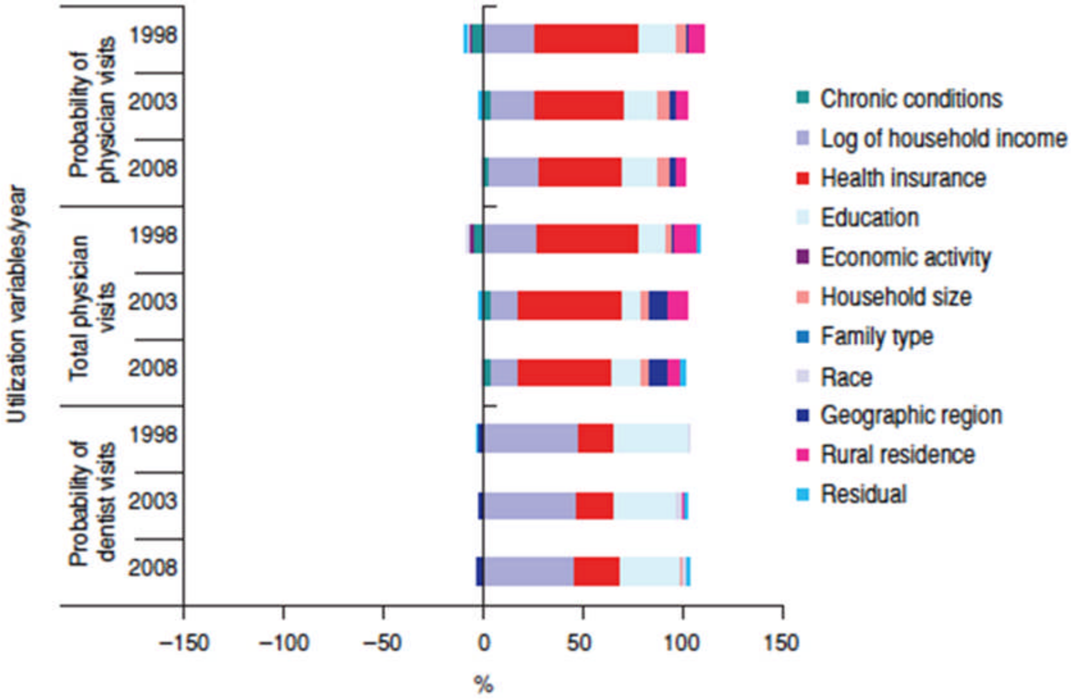
Variable	1998		2003		2008		HI difference	
	CI	HI	CI	HI	CI	HI	1998–2003	2003–2008
Self-assessed health (less than good)	−0.1460	−0.1064	−0.1432	−0.1333	−0.1408	−0.1312	−0.0270[a]	0.0022[a]
Physical limitation (any)	−0.0880	−0.0398	−0.0591	−0.0420	−0.0571	−0.0385	−0.0022[a]	0.0035[a]
Chronic illness (any)	−0.0397	0.0028	0.0252[a]	0.0514[a]	0.0185[a]	0.0482[a]	0.0486[a]	−0.0032
Physician visits (probability)	0.0514[a]	0.0724[a]	0.0518[a]	0.0653[a]	0.0398[a]	0.0518[a]	−0.0071[a]	−0.0135[a]
Physician visits (total)	0.0656[a]	0.1200[a]	0.0581[a]	0.1030[a]	0.0429[a]	0.0868[a]	−0.0170[a]	−0.0162[a]
Hospitalization (probability)	−0.0767	−0.0104	−0.0470	0.0128	−0.0411	0.0189	0.0231[a]	0.0061
Hospitalization (days)	−0.0856	0.0239	−0.0367	0.0623	−0.0413	0.0430	0.0383[a]	−0.0192[a]
Dentist visits (probability)	0.2228[a]	0.2266[a]	0.1873[a]	0.1988[a]	0.1472[a]	0.1590[a]	−0.0278[a]	−0.0398[a]

CI: concentration index, HI: horizontal index.
[a] Significant CI and HI indices ($P < 0.05$).

Source: Almeida et al, 2013.

The authors go further in the analysis and decompose the measure of inequality. Figure 3.3 shows that the most important contributors to income-related inequality in healthcare use are health insurance, income, education and urban status.

Figure 3.3 – Decomposition of the Horizontal Inequity Index, for healthcare use



Source: Almeida et al, 2013.

3.5 Evidence about mammography and cervical screening for women in low, middle and high income countries

Finally we cover studies of inequality in preventive care for women. As Rossi et al have demonstrated, inequality in preventive care is often found to be pro-rich (Rossi et al., 2009). We focus on cervical and mammography screening, which are the variables of interest in this thesis. We have selected two major national studies, one a middle income country (Mexico) and one in high income country (England), and one major international study in Europe – to date, no international study has compared equity in preventive care for women between multiple low and middle income countries. All in all, the studies demonstrate that inequality in cervical and mammography screening exist, both in developed and developing nations (Couture et al., 2008, Rossi et al., 2009, Palencia et al., 2010). There is also evidence that inequality in use of these forms of care is larger in countries where screening is only opportunistic (Palencia et al., 2010).

3.5.1 Inequalities in breast and cervical cancer screening among urban Mexican women *by Marie-Claude Couture, Cat Tuong Nguyen, Beatriz Eugenia Alvarado, Luz Delia Velasquez, Maria-Victoria Zunzunegui (2008)*

The goal of the study conducted by Couture et al was to establish a relationship between socio-economic and demographic factors and the likelihood of getting a cervical or a mammography screening. In terms of data, they have used the SABE/PAHO survey, which evaluated the health and wellbeing of the elderly in seven cities in Latin America (Albala et al., 2005). As they have focused on Mexico, only the information for Mexico city was used.

Unlike many inequality studies, the authors chose not to use a synthetic measure to report inequality, but rather have relied on the odds ratios resulting from the standardising logistic regressions. Three different models were built. In the first, the authors controlled for what they called predisposing factors, which included age, marital status, education and occupation. The second model also used enabling factor as covariates (Couture et al., 2008), namely perception of having (in)sufficient income and coverage by health insurance, categorized by type of insurance. And finally, the third model included need in the form of self-assessed health and previous examination in the past two years.

Table 3.8 below presents the results. It shows that the inclusion of variables decreases the importance of education as a predictor for receiving care. It also shows that private health insurance is a strong predictor of getting mammography screening, although the same cannot be said for other forms of insurance. Finally, whereas need does not appear to be a strong predictor of preventive care, having had a clinical breast test in the past two years increases significantly the chance of getting a mammogram.

Table 3.8 – Odds ratios and confidence intervals of the standardising logistic regressions for mammography, as proposed by Couture et al (2008)

	Model 1		Model 2		Model 3	
	OR	95% CI	OR	95% CI	OR	95% CI
Predisposing						
Education						
Post-secondary vs illiterate	5.52	3.21–2.46	4.48	2.50–8.03	1.83	0.97–3.45
Secondary vs illiterate	2.64	1.43–4.68	2.30	1.22–4.34	1.11	0.55–2.24
Primary vs illiterate	1.51	0.92–9.48	1.42	0.86–2.37	0.96	0.55–1.66
Marital status						
Single vs married	2.19	1.25–3.84	2.12	1.17–3.81	2.58	1.29–5.15
Widowed vs married	1.57	1.09–2.24	1.53	1.06–2.21	1.72	1.15–2.57
Divorced/separated vs married	1.37	0.87–2.16	1.47	0.92–2.33	1.70	1.01–2.89
Enabling						
Perception of income						
Sufficient vs insufficient			1.17	0.85–1.63		
Insurances						
Private vs none			3.63	1.69–7.79	3.08	1.29–7.33
Civil servants vs none			1.03	0.63–1.69	0.92	0.53–1.61
Public vs none			1.12	0.76–1.66	0.79	0.51–1.22
Need						
Perceived health						
Good to excellent vs poor					1.03	0.59–1.80
Fair vs poor					0.93	0.56–1.55
Breast self-examination over the last two years						
Yes vs no					1.85	1.16–2.95
Clinical breast examination over the last two years						
Yes vs no					14.94	8.47–26.34

Source: Couture et al, 2008.

3.5.2 Inequalities in reported use of breast and cervical screening in Great Britain: analysis of cross sectional survey data *by Kath Moser, Julietta Patnick, Valerie Beral (2009)*

The study published on the British Medical Journal (BMJ) investigates the presence of inequality by looking at the relationship between the reported use of breast and cervical screening and some socio-demographic characteristics. To perform the analysis, it uses a sample of 3185 women aged 40 to 74, which were interviewed in the National Statistics Omnibus Survey between 2005 and 2007.

Again, although they are interested on socio-economic inequality, they do not report a synthetic measure, but rather the odds ratios of standardizing regressions. They also have a non-standard approach in terms of socio-economic ranking, as they do not use income, but prefer number of cars in the household and housing tenure (rent, own with mortgage and own outright) as indicative of socio-economic status. Other covariates used include: education, the National Statistics' socio-economic classification for occupation, ethnicity and region.

Their findings suggest that indeed inequality in both preventive forms of care exists in the UK. For the case of mammography, women living in owned households with cars are more likely to get screened, but there is no statistically significant difference in terms of education, occupation ethnicity and region. In term, cervical screening is more likely for white British women and higher education implies higher use of this form of care. Nonetheless, socio-economic status does not appear to play a role, nor does region (Moser et al., 2009).

In the conclusion, the authors highlight possible policy implications of their findings and defend that routine data collection of socio-demographic information from patient could help monitoring and improving inequality.

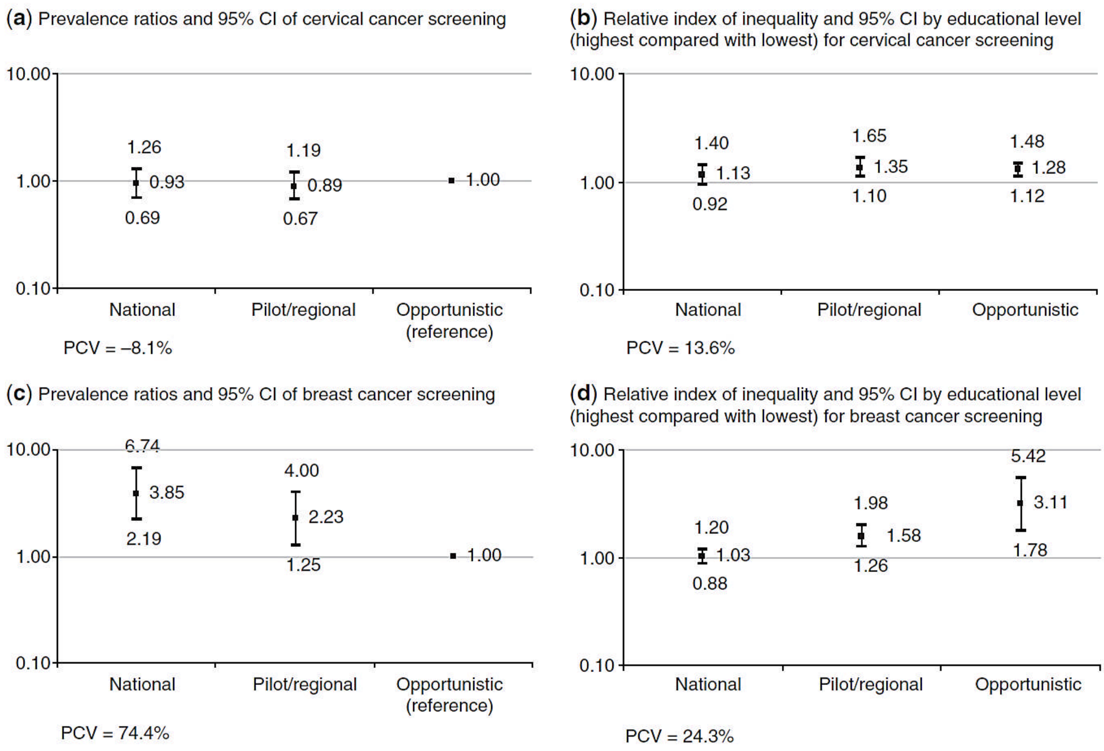
3.5.3 Socio-economic inequalities in breast and cervical cancer screening practices in Europe: influence of the type of screening program *by Laia Palencia, Albert Espelt, Maica Rodrıguez-Sanz, Rosa Puigpinos, Mariona Pons-Vigues, M Isabel Pasarın, Teresa Spadea, Anton Kunst and Carme Borrell (2010)*

This final study was chosen to be reviewed due to its comprehensiveness. The authors have investigated the existence of socio-economic inequality and its relationship with the type of screening programme (if any) performed by each country in 21 different nations, being 20 in Europe (Austria, Belgium, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Luxemburg, Portugal, the Netherlands, Slovenia, Spain, Sweden and the UK) and Israel. For the analysis, the authors have used education as a socio-economic variable, and covariates included age, marital status, urban or rural residency, work status and perceived health.

The analysis was performed as cross-section, using data from WHO World Health Survey. The selection criteria included women aged 25-69 for cervical cancer screening and 50-69 for breast cancer screening.

Given that the main objective of the authors was not only de-flagging inequality but also investigating its relationship with the type of cancer screening programme run in each nation, they have compiled prevalence ratios, setting countries were screening is only opportunistic as reference group, and produced a relative index of inequality. Figure 3.4 presents the results of their findings.

Figure 3.4 – Prevalence ratios and Relative Index of inequality, by type of screening programme



As we can see from the figure, although not much inequality is found for cervical screening, for mammography inequality is relatively large for countries were only opportunistic screening is in place (Palencia et al., 2010). Their findings suggest that having a national cancer screening programme in place decreases socio-economic-related inequality, at least in Europe.

Table 3.9 – Summary of the empirical evidence

Study	Year	Region	Main findings
Van Doorslaer et al	2004	OECD	- Small pro-poor horizontal inequality for GP visits in 10 countries. - Pro-rich inequality in Specialist visits. - Large pro-rich inequality of overall outpatient care in circa 10 countries. - Mixed evidence of inequality in inpatient care
D'Uva, Jones and van Doorslaer	2009	Europe	- For GP visits, all countries display pro-poor inequality, with the exception of Austria, Portugal and Finland. - For specialist visits, all nations present pro-rich inequality.
Devaux and de Looper	2012	OECD	- All countries present a small pro-rich inequality for doctor's visit. Only in the US is the index large. - In 9 of the countries studied no evidence of inequality in GPs visit is found. - In all countries, pro-rich inequality of specialist visit was observed. - Almost all countries displayed pro-rich inequality for breast cancer screening. - Certain system features have an important impact on equity.
Suárez-Berenguela	2000	Latin America and Caribbean	- Pro-rich inequality in all countries. - Smaller measure of inequality in curative care when compared to preventive care. - For Brazil, the measure for chronic illnesses is the smallest, even though it is still pro-rich.
Balsa, Rossi and Triunfo	2009	Latin America	- Pro-rich inequality of doctor's visit of different magnitudes. - Larger pro-rich inequality in preventive care than in curative care. - Mixed evidence in quality of care.
Campino et al	2001	Brazil	- Evidence of inequality in health, health care utilization and health care financing has been found, and it favours in general the well-off population. - In the case of health care use, pro-rich inequality was found for curative, preventive and care of chronic illnesses.

			- Inequality reaches its greatest magnitude in the use of preventive services.
Giatti and Barreto	2006	Brazil	- A strong relationship between the individual's insertion in the labour market and his health exists. In general, formal works enjoy better health than their informal counterparts. The worst indicators are obtained for individuals outside the labour market. - The relationship between health care use and labour market insertion is less unequivocal.
Uga and Santos	2007	Brazil	- In general the financing of health care in Brazil is neutral, as progressivity in public expenditure is counteracted by regressivity in private spending. - Out-of-pocket spending is particularly regressive, which may cause impoverishment.
Macinko and Lima-Costa	2012	Brazil	- Inequality of doctor's visits, usual source of care, any use of healthcare and dental visits is pro-rich through the period of analysis. - Inequality of hospitalizations is pro-poor throughout the period of analysis. - For the four outcome variables analysed, inequality has decreased between 1998 and 2008 - Inequality reaches its largest in the use of dental services.
Almeida et al	2013	Brazil	- In terms of health, inequality is pro-poor for self-assessed health and physical limitations. But goes from pro-poor in 1998 to pro-rich in 2003 and 2008 for prevalence of chronic conditions. - In terms of health care, inequality is pro-rich for physician and dentist visits, but pro-poor for hospitalization, when measured by the standard CI. - Inequality in healthcare utilization is decreasing for all three outcome variables, when measured by the HI. - The main contributors to inequality are health insurance, income, education and urban/rural residency.

Couture et al	2008	Mexico	- There is a positive association between preventive care in the forms of mammography and cervical screening and education, coverage by health insurance and previous preventive procedures, such as clinical breast examinations, in women aged 50 or over. - Need factors do not appear to be indicative of higher use of preventive care.
Moser et al	2009	Great Britain	- Inequality exists for both mammography and cervical screening in the UK. - For mammography, predictors of high-use include living in an owed household and having cars (measures of socio-economic status). - For cervical screening, predictors of high-use include being white British and more educated.
Palencia et al	2010	Europe	- Socio-economic inequality exists in Europe, where cancer screening programmes are concern. - The measure of inequality in terms of a relative index of inequality is relative large for mammography in countries where only opportunistic screening takes place. - Countries with a national screening programme appear to have smaller inequality, both in terms of breast and cervical screening.

Source: Compiled by the author.

PART 2: APPLIED RESEARCH

Chapter 4: Measuring overall inequity in health care: an empirical application to physician visits in Brazil

Abstract

This chapter develops and applies a new approach to measuring inequity in health care, which I call multivariate because it looks at multiple sources of unjust inequality. The multivariate approach generalises the standard bivariate approach by allowing simultaneously for multiple dimensions of "unfair" social variation in health care, and then decomposing the contribution of each dimension to overall inequity. My proposed approach encompasses the standard bivariate concentration index approach as a special case in which the only unfair dimension of inequality is income. The approach is illustrated through an application to 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. I find that overall inequity is much larger than income-related inequity, and that health insurance coverage and urban location both contribute more to overall inequity than income. In terms of contribution, the material presented in this chapter innovates in three fronts: firstly, it applies the multivariate framework to measuring overall unfair inequality in health care, as opposed to income-related inequality, which to our knowledge has not been done so far; secondly, it uses a developing country to its application, which per se is interesting when measuring inequalities; and finally, it corrects possible biases from work conducted previously on Brazilian inequality.

4. 1 Introduction

In the wake of the global universal health coverage movement, the issue of equity and inequality in health care is high on the policy agenda in low, middle and high-income countries (Evans and Etienne, 2010, WHO, 2013). Over the past twenty years not only has the number of publications in this area increased exponentially, but its methods have also developed rapidly, allowing for more accurate measures and hence better information for policy makers (O'Donnell et al., 2008). Economists have developed better methods both for measuring inequality and for identifying the determinants or even causes of inequality (Rosa Dias, 2009).

During the 1990s and 2000s, economic research on inequality in health and health care focused on "bivariate" measures of inequality. Bivariate measures are based on the relationship between two variables: a health variable and a single social variable considered to represent a source of "unfair" inequality, most frequently income. More specifically, the European Ecuity project team 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 (O'Donnell et al., 2008). Several researchers have subsequently refined this approach, resulting in a proliferation of indexes including the horizontal inequity index, the Erreygers concentration index (Erreygers, 2006, Erreygers, 2009), the generalized concentration index (Wagstaff, 2005) and the extended one (Wagstaff and Watanabe, 2003).

Lately, researchers have started to examine “multivariate” measures of health inequality, which allow simultaneously for multiple unfair sources of inequality in health (Norheim and Asada, 2009), though this has hitherto mostly been applied to inequality in health outcomes rather than inequality in the delivery of health services. The phrase “multivariate inequality measure” from the equity literature is not to be confused with the phrase “multivariate regression” from the statistics and econometrics literature, which refers to the use of multiple outcome variables. Furthermore, it should also be distinguished from the different strand of research on “multidimensional inequality measures, involving inequality in the distribution of multiple different goods – such as income, health, education and others (Atkinson, 1982, Lugo, 2005). In the context of inequality in health, work 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 chapter, an adapted version of the basic idea of factors for which an individual can (not) be held responsible can be applied to the case of equity in health care, by distinguishing between “fair” sources of variation in health care such as individual needs and preferences, and “unfair” sources of variation that should not influence the use of health care.

In this chapter, I develop a new multivariate approach for measuring overall unfair inequity in health care, using Brazil as an illustrative example. Brazil is an interesting case study due to its large population (more than 200 million inhabitants in 2014), middle-income status and highly unequal distribution of income– with a Gini of 54.6 (Bank, 2009).

The chapter contributes to knowledge in three ways. First, it contributes to methodology by providing the first application of the Fleurbaey and Schokkaert multivariate approach, hereafter referred to as the “FS approach”, to measuring overall unfair inequality in health care (Fleurbaey and Schokkaert, 2011). To our knowledge, although the multivariate FS 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 FS 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. This provides summary indices and decompositions that can be compared to traditional bivariate measures, and are arguably more comparable across studies and settings. Thirdly, the paper addresses a potential bias in previous studies of equity in health care in Brazil. This paper presents descriptive statistics showing substantially higher rates of self-reported chronic illnesses in higher socioeconomic groups. This suggests that chronic conditions are substantially misrepresented or under-diagnosed in socially disadvantaged individuals in Brazil, 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, and due to substantial under-diagnosis this may therefore under-estimate the degree of health care inequality. We address this by focusing on age, sex and self-assessed health alone as the main need standardising variables. Even though self-assessed health is a variable that may suffer from reporting bias, studies have shown it to be both a good indicator of health as well as of health care us.

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

The next section presents the theoretical background. The third section describes the data and methods. The fourth section presents the results, highlighting similarities and differences between the multivariate approach for measuring overall unfair inequality and the bivariate approach for measuring income-related inequality, including the proposed health care advantage rank and a decomposition analysis of the contribution of different factors to overall inequity in health care. The final section concludes.

4.2 Theoretical Background

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

$$\mathrm{h}c_{\mathrm{i}} = \mathrm{hc}\,(\mathrm{N}_{\mathrm{i}}, \mathit{SES}_{\mathrm{i};}\, \mathrm{X}_{i}) \qquad [1]$$

That is, health care (hc) is a function of need variables (N), which may include age, sex and health status variables, socioeconomic status (SES), and a vector of other non-need variables, X, 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, but that socioeconomic status is not. 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 socioeconomic status, after purging the influence of confounding variables and adjusting for fair variation associated with need.

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, continue to rely on reduced form econometric modelling of associations rather than structural econometric modelling of causal pathways.

Once we are concerned with overall unfair inequality, that is, inequity deriving from multiple sources, 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 causal associations. Thus, we can consider a reduced form health care utilisation function of the form $hc(f_i, u_i, n_i)$, where f_i denotes variables that produce fair inequalities in health care, u_i corresponds to unfair sources of inequality, and n_i corresponds to neutral variables. Commonly, the socioeconomic inequality literature assumes that $f_i = (N)$, $u_i = SES$, 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 as a potential "fair" source of variation. Thus, as Fleurbaey and Schokkaert (2012) have proposed, it may be more useful to consider $f_i = (N, P)$ 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, Z_i for other variables considered "unfair", and 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 this thesis, 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 does the choice of reference values when adjusting for "fair" variation. In the scope of this work, both needs (N) and treatment preferences (P_i) were considered fair.

When measuring inequality in health, one can apply the theory of equality of opportunity to help classify variables into these three categories (fair, unfair and neutral). So, for example, inequalities may be considered "fair" if they derive from choices for which an individual is considered responsible, for example choices about human capital investment, financial investment, employment, consumption and lifestyle. In contrast, inequalities are considered "unfair" if they derive from circumstances for which the individual is not considered responsible, for example their age and sex, ethnicity, genetic inheritance, parental wealth, social position and parenting style, and so on (Fleurbaey and Schokkaert, 2011). This differentiation allows the analyst to assess how far variation in success between different individuals is unfair, enabling different value judgements about how far the individual is held responsible for different factors. The case of health care is somewhat different, as one cannot use the idea of individual responsibility in the same way to guide judgements about what counts as "unfair" source of variation in health care utilisation.

This specification allows for both the direct effect of socioeconomic variables on health care, and the indirect effect that passes through health care needs. This may give rise to a correlation between fair and unfair factors contributing to inequality. If that is the case, the researcher must make a normative decision and establish whether to take into consideration preferences.

A central issue is then how to move from the measurement of overall inequality to unfair inequality only (Van Kippersluis et al., 2009, Lefranc et al., 2009, Trannoy et al., 2010). Two measures have been proposed to resolve this issue and measure unfair inequality only, namely i) direct unfairness and ii) the fairness gap. According to FS, direct unfairness reflects the principle that "a measure of unfair inequality should not reflect legitimate variation in outcome, i.e. inequalities which are caused by differences in responsibility variables" (Fleurbaey and Schokkaert, 2009). Practically, this measure eliminates the fair sources of inequality by setting them at reference values and predicting the outcome based on unfair determinants only. In the case of inequality in health care, direct unfairness can be calculated as follows:

$$\mathrm{hc}_{\mathrm{i\_du}} = \mathrm{hc}_{\mathrm{i\_predicted}}\,(N_{ref},\ P_{ref}, SES_i, Z_i; X_{ref}) \qquad [3]$$

Where $\mathrm{hc}_{\mathrm{i\_predicted}}$ 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 be argued that sex is a need variable, and therefore, fair, as maternal care, for example, is a legitimate reason for women to receive more health care than man. Hence, in our analysis, there are no neutral variables, which allows equation 3 to be reduced to:

$$\mathrm{hc}_{\mathrm{i\_du}} = \mathrm{hc}_{\mathrm{i\_predicted}}\,(N_{ref},\ P_{ref}, SES_i, Z_i) \qquad [4]$$

Turning our attention to the fairness gap, this satisfies the egalitarian equivalence principle that when or if a "measure of unfair inequality is zero, there should be no illegitimate differences left" (Fleurbaey & Schokkaert, 2009). Again for the case of health care, the formula for the fairness gap for the evaluation of absolute inequality is given by:

$$\mathrm{hc}_{\mathrm{i\_fg\_a}} = \mathrm{h}c_i - \mathrm{h}c_{i\_predicted}\,(N_i,\ P_{i,}\ SES_{ref}, Z_{ref}; X_{ref}) \qquad [5]$$

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, after purging the influence of neutral X variables. As before, given that no neutral variables are defined in our empirical exercise, equation 5 can be reduced to:

$$\mathrm{hc}_{\mathrm{i\_fg\_a}} = \mathrm{h}c_i - \mathrm{h}c_{i\_predicted}\,(N_i,\ P_{i,}\ SES_{ref}, Z_{ref}) \qquad [6]$$

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 FS, 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, his individual measure of health care from which one may calculate <u>overall unfair</u> inequality.

Unlike the measure of direct unfairness, the fairness gap (ratio) has different specifications for absolute and relative inequality. Equations 5 and 6 present the specification in absolute terms. For the relative case, in the reduced form, where no neutral variables exist, the fairness gap is actually a ratio and can be defied as:

$$\mathrm{hc}_{\mathrm{i\_fg\_r}} = \mathrm{h}c_i\,/\,\mathrm{h}c_{i\_predicted}\,(N_i,\ P_{i,}\ SES_{ref}, Z_{ref}) \qquad [7]$$

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., 2014, 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 basically 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. Inclusion of residual variation would substantially and artificially inflate the fairness gap, making it incomparable with direct unfairness, which does not include residual variation. Nonetheless, the chosen treatment implies that I am implicitly considering the stochastic “noise” or “luck” to be fair and not to include it in the resulting measure of overall 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 I 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 overall unfair inequality can be derived.

4.3 Methods

4.3.1 Fair and unfair factors

I use three different criteria to distinguish between “fair” and “unfair” factors. The first model, hereafter referred to as the basic model, establishes a 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. It allows for a relationship between overall unfair inequality and income-related inequality to be demonstrated. If the only source of unfairness in a model is income, then the measure of overall unfair inequality must be equal to that of income-related inequality. This model serves as a baseline and allows for comparisons with the traditional bivariate approach, for which inequality in physician visits in Brazil has already been calculated.

The second model, called intermediate, also includes non-need factors, placed in the z vector – namely, educational achievement, ethnicity and region. These are considered relevant due to the relationship between such variables and both health and health care, measured by self-assessed health and physician visits in the past year (any physician visit in the past 12 months), respectively. Although I treat income as the primary socioeconomic variable, rather than education, this is purely for purposes of comparison with the standard bivariate approach – my approach allows us to examine both sources of unfair inequality on an equal footing. This model is run, primarily, as a pedagogical exercise, with the objective of understanding the differences between the Fleurbaey and Schokkaert approach for measuring overall unfair inequality and the traditional bivariate approach for measuring income-related inequality. Even though the intermediate is arguably not the best possible model estimation, it explicitly does not include private health insurance. In the Brazilian health system, private health insurance is supplementary and does not alter the universal coverage status from the public health system. In Brazil, private health insurance can be directly purchased by individuals, but most people (74.9% of the insured in 2008) who have private health insurance do so by means of employment (Pietrobon et al., 2008), which implies that the insurance is purchased by their employers. Due to legislation, large companies (more than 500 employees) must provide private health insurance coverage as a benefit to all employees, regardless of their level within the company. Thus, it has been argued in the Brazilian literature that, while measuring inequality in healthcare, one should not take private health insurance into account (Sousa, 2002, Mendes, 2012, Marques and Mendes, 2016, Barbosa, 2013). Therefore, this model provided a useful exercise in transitioning from the measurement of income-related inequality to overall unfair inequality.

Finally, my comprehensive model is perhaps the best possible model specification. It also includes several other non-need variables in the unfair vector such as employment status, an urban/rural dummy, family type and health insurance coverage. Furthermore, it includes seatbelt use as a fair variable. This latter variable was chosen as a proxy for preferences for healthcare seeking, on the grounds that one's 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 healthcare. In other words, one's behaviour towards risk may explain health care seeking behaviour (Hersch and Pickton, 1995, Dardanoni and Wagstaff, 1987).

If one took the view of Fleurbaey and Schokkaert, one should focus on the results from comprehensive model, and although I have considered private health insurance to be unfair, one potentially could place this variable in the fair vector if, for example, one believes that being insured is purely voluntary matter of "choice". To some extent, the decomposition analysis performed in this chapter allows for different normative perceptions regarding fair and unfair variables. Notwithstanding, the results from the other models may provide some insight on the transition from measuring income-related inequality to overall unfair inequality.

4.3.2 Measurement of overall inequality in health care: a modified concentration index

So far, applications of the FS 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 augmenting the approach proposed by Fleurbaey and Schokkaert and going beyond the variance with an additional bivariate-type approach that the health policy community 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 literatures, and hence, a bivariate approach (a) facilitates comparison between different studies and (b) facilitates the relevant people (academics, policy advisers and policy makers) understanding the meaning of the measure. Although we explore other bivariate measures in sensitivity analysis – in particular, gaps and ratios between top and bottom group – we focus on one class of (relative) bivariate measure for our detailed analyses: the concentration index (and the Erregyers modification thereof). Our use of concentration indices for this purpose can be justified for three reasons: i) it can be compared in both magnitude and decomposition with the results of concentration-index-type approaches for measuring income-related inequality 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) a as a mean independent measure, the concentration index allows for measures of inequality in different forms of health care to be compared. Therefore, whilst we compute the variance to obtain a measure of absolute inequality in this chapter, when comparing different forms of health care use, we favour the concentration-index-type measure. Furthermore, gaps and ratios between quintile groups are also calculated, as they are easy for policy makers to interpret and the gap measure also provides a simple measure of absolute inequality to complement the measure of relative inequality provided by the concentration index. Finally, we acknowledge that other bivariate measures could also be computed, such as slope and relative indices, and decision makers may find these useful in particular contexts.

Hence, the proposed method for measuring inequality makes use of the traditional bivariate framework, while incorporating the multivariate measures of "direct unfairness" (hc_{i_du}) and the "fairness ratio" ($hc_{i\_fg\_r}$). Within the bivariate measures, I have focused on the concentration index for the base-case analysis. As the concentration index frameworks refers to relative measures of inequality, both direct unfairness and the fairness gap must be defined in relative terms, which in the second case, consists of a fairness ratio. The correct specification of both measures follows equations 4 and 7, respectively.

Intuitively, to look at overall unfair inequality as opposed to income-related inequality, one should rank people according to their health care advantage relating to multiple sources of unfairness instead of ranking people in terms of their position in socioeconomic status.

Effectively, this can be done by replacing the income rank in the x-axis with a ranking created using one of the multivariate measures i.e. either direct unfairness (hc_{i_du}) or the fairness ratio ($hc_{i\_fg\_r}$). This ranks people by how likely they are to receive appropriate care due to unfair advantages, with people towards the right having a greater "unfair" access to health care than people towards the left. 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 his level of need and treatment preferences.

We then apply any bivariate measure of inequality, including the standard concentration index apparatus and the usual standardisation procedures, the slope index of inequality or extreme group measures, using the HCA rank as the ranking variable, rather than the traditional ranking variable of income, to examine how far the share of health care received is related to Health Care Advantage Rank.

In this chapter, 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 of using direct unfairness was simply computational ease, as the same specification can be used for the relative and absolute cases.

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: the directly standardised concentration index (CI), the horizontal inequality index (HI), which is equivalent to the indirectly standardised concentration index and the Erreygers modified concentration index, based on the directly standardised concentration index, due to its mirror, monotonicity and level of independence properties (Erreygers, 2009).

The estimation of the directly standardised concentration index deserves some further attention, as it relates to FS original proposition of taking a (generalised) Lorenz-curve approach to measuring inequality using direct unfairness and the fairness gap. In fact, using direct unfairness as a reference, the measure of relative inequality using a Lorenz-curve approach would consist of a Gini coefficient and be defined as:

$$G_{du} = \frac{2\,\mathrm{Cov}\,(hc_{i\_du}, F(hc_{i\_du}))}{\mu_{hc\_du}} \qquad [8]$$

where hc_{i_du} is the individual measure of health care as estimated by direct unfairness, $F(hc_{i\_du})$ is the cumulative distribution function of direct unfairness and μ_{hc_du} is the mean level of direct unfairness across the population. The directly standardised CI using my proposed method relates to this approach. In fact if we recall the formula for direct standardisation, formalised in equation 9 below, we can see that it is equal to that of direct unfairness (equation 4):

$$hc_{i\_direct} = hc_{i\_predicted}\ (N_{ref},\ P_{ref}, SES_i, Z_i) \qquad [9]$$

Thus, the directly standardised concentration index of health care on direct unfairness is given by:

$$CI_{direct} = \frac{2\ Cov\ (hc_{i\_direct}, F(hc_{i\_du}))}{\mu_{hc}} \qquad [10]$$

where hc_{i_direct} is the directly standardised individual measure of health care, $F(hc_{i\_du})$ is the cumulative distribution function of direct unfairness and μ_{hc} is the mean level of health care across the population. Given that $hc_{i\_direct} = hc_{i\_du}$, one can write the proposed measure of inequality as a function of the Gini.

$$CI_{direct} = \frac{2\ Cov\ (hc_{i\_du}, F(hc_{i\_du}))}{\mu_{hc}} \times \frac{\mu_{hc\_du}}{\mu_{hc\_du}} \qquad [11]$$

$$CI_{direct} = \frac{2\ Cov\ (hc_{du}, F(hc_{du}))}{\mu_{hc\_du}} \times \frac{\mu_{hc\_du}}{\mu_{hc}}$$

$$CI_{direct} = \frac{\mu_{hc\_du}}{\mu_{hc}} \times G_{du} \qquad [12]$$

If $\mu_{hc\_du} = \mu_{hc}$, then my proposed approach and the Lorenz-curve approach, suggested by Fleurbaey and Schokkaert, coincide. This is to be expected in linear models with no interactions where the reference values for direct unfairness variables are set at the mean level of the population. If not, and in fact if $\mu_{hc\_du} < \mu_{hc}$, as is our case, then my proposed measure of overall unfair inequality is smaller than that suggested by Fleurbaey and Schokkaert. If plotted in separate graphs, the Gini coefficient would have the cumulative proportion of direct unfairness in the y-axis, whilst the proposed concentration index would have the cumulative proportion of health care in the y-axis. However, given that a relationship can be found between the directly standardised concentration index for health care and the Gini, one could plot both in the same graph. The relationship between both indices is expressed in terms of different means, although *per se* both measures are mean independent, i.e. it is the relationship between the indices that is a function of different means, and not the indices on their own.

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 healthcare received, allowing for the "appropriate" level of health care given the individuals' needs and treatment preferences. This is the equivalent of indirect standardisation. The latent variable is predicted following each of the model specifications, as defined previously in this Chapter. Mathematically, the Horizontal Inequity Index is defined as:

$$HI = CI - CI_{needpredict} \qquad [13]$$

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

$$HI = \frac{2\,Cov\,(hc_i, F(hc_{i\_du}))}{\mu_{hc}} - \frac{2\,Cov\,(hc_{i\_needpredict}, F(hc_{i\_du}))}{\mu_{hc\_needpredict}} \qquad [14]$$

Finally, the need predicted function that defines $\underline{hc_{i\_needpredict}}$ is:

$$hc_{i\_needpredict} = hc_{i\_predicted}\,(N_i, P_i, SES_{ref}, Z_{ref}) \qquad [15]$$

Unlike equation 10, the prediction formulated in equation 15 holds socioeconomic status and other unfair variables at reference level, while allowing for need and treatment preference variables to vary.

Had we used the fairness gap, defined in absolute terms, to produce the HCA rank, a similar relationship to that defined in equation 12 between HI and the (absolute) Gini would also exist. However, using the fairness ratio (relative) specification, such relationship does not emerge, given that its specification is different to that of indirectly standardised healthcare, as can be seen in the equations below.

$$hc_{i\_fg\_r} = hc_i \,/\, hc_{i\_predicted}\,(N_i, P_i, SES_{ref}, Z_{ref}) \qquad [16]$$

$$hc_{i\_indirect} = hc_i - hc_{i\_predicted}\,(N_i, P_i, SES_{ref}, Z_{ref}) + \mu_{hc} \qquad [17]$$

where equation 16 specifies the fairness ratio and equation 17 the indirectly standardised healthcare, respectively.

Last but not least, the choice of reporting the three indices is an acknowledgement to the fact that there is a heated debate as to which is the most adequate index to use, both when the outcome variables are binary or continuous (Wagstaff, 2011a, Wagstaff, 2011b, Erreygers and Van Ourti, 2011b, Erreygers and Van Ourti, 2011a). Our choice of reporting three different formats 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 overall 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 suite also allows us to decompose the contribution of each “fair” and “unfair” source of inequity (O'Donnell et al., 2008). The intuition behind the decomposition is looking at the contribution of each factor into the measure of inequality. Since we are interested in overall unfair inequality, it would be interesting to look at how much each unfair factor contributes to the overall index. This can also be understood as a form of sensitivity analysis, with regards to different normative positions around unfair inequality. The decomposition used in this thesis is done by calculating the marginal impact of neutralising the variable of interest, i.e. the factors in the decomposition, on the concentration index (Yiengprugsawan et al., 2010, O'Donnell et al., 2013). 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, which examines how a certain payoff should be allocated amongst a set of players in relation to their contribution (Shorrocks, 2013). Considering that the proposed measure of overall unfair inequality fall into the concentration index category, the interpretation of the decomposition is analogous to that performed in income-related inequality.

4.4 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 Portuguese, the survey is referred to as the National Household Sample Survey (*Pesquisa Nacional por Amostra de Domicílios* or PNAD). Even though this survey is carried out every year – with the exception of years when Census are held (every 10 years in Brazil) – health and health care variables are only collected once every 5 years as part of the Health and Health Care supplements performed in collaboration with the Ministry of Health. In total, three waves have been published (1998, 2003, 2008). In 2013, a new Health Survey has set up and put in place. As this paper was written before the release of the 2013 data, the method was applied using the most recent wave to date. To define its sample, PNAD makes 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. All health related variables rely upon self-report.

According to the methodological guidelines of the survey used, only two variables included in one or more of the models were directly observed, region and an urban and rural dummy. All other variables, including income, ethnicity and sex, rely on self-report. The variable income refers to the log of household income equivalised following the square root scale, as advocated by OECD publications. Self-assessed health could be reported in five categories ranging from very bad to very good. We chose to include education in terms of highest qualification achieved, due to the fact that in Brazil it is not uncommon for individuals to attend school for a number of years and not achieve the correspondent educational level. Other important variables such as private health insurance coverage and employment were dummies, although for the latter we choose the broad concept of employment, meaning that any differences due to the form of employment (permanent position, temporary contract, self-employment, informal market, etc) are not captured.

Before we turn our attention to the results of the multivariate analysis, we highlight some features of the data that may help in the interpretation of the inequality measures.

4. 5 Descriptive Statistics

Brazil is a middle-income country of large geographical proportions, rich in natural resources. The Amazon river and the Amazonian rainforests are perhaps the most iconic symbols of the biodiversity that can be found within the Brazilian borders. The large magnitudes of the country impose a difficulty in terms of supplying health care, as some regions are remote and difficult to reach. Furthermore, it also common knowledge that Brazil, throughout its history, has experienced large income inequality and there is a multimillion segment of its population living in poverty or extreme poverty.

When analysing inequality of any kind, one should not forget the general features that hold unique to a region. They could point some basic directions and provide guidelines for the interpretation of the phenomena observed. This is exactly the objective of this session – to present some basic descriptive statistics obtained from the survey data we use to measure inequality in health care. It should provide hints to the interpretation of unfair inequality in health care.

4.5.1 Income, Ethnicity and Education in Brazil

Previous studies on inequality in Brazil have demonstrated that the distribution of wealth and income within the nation is far from being equal (Ferreira et al., 2016, Azzoni, 2001, Ferreira and Gignoux, 2011). Therefore, as income is one of the factors producing unfair inequality, one should attempt to minimally recognise patterns of income distribution. Table 4.1 expresses equivalised household income and coverage by private health insurance, by month (according to the square root scale, currently used in OECD publications).

Table 4.1 – Equivalised Household monthly Income (In local currency of 2008) and Health Insurance cover (%) by group

Equivalised Household Income by Group	Mean	SD	Health Insurance
Q1 - Poorest 20%	188	83.60	3.5%
Q2 - Second poorest 20%	404	59.30	8.7%
Q3 - Middle 20%	631	73.72	16.7%
Q4 - Second Richest 20%	997	154.17	30.3%
Q5 - Richest 20%	2,880	2343.39	62.2%
D10 - Richest 10%	4,144	2804.74	72.8%
V20 - Richest 5%	5,841	3298.25	79.7%
P100 - Richest 1%	11,084	4426.18	86.1%
Total	1,050	1456.083	24.5%

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

The table clearly demonstrates that income and private health insurance coverage are indeed unevenly distributed within the nation and that they are positively correlated. This is to be expected, as in Brazil private health insurance can be bought individually. However, most private health insurance coverage (circa 75%) in Brazil is employment-related, that is, secured and paid by the employer. This establishes an indirect relationship between private health insurance coverage and income. It can be argued that people who are better employed are more likely to be insured by the organisation they work for. Nonetheless, if they are better employed, they are also more likely to be in the upper quintile groups of income. It can be argued that people who are better employed are more likely to be insured by the organisation they work for. Nonetheless, if they are better employed, they are also more likely to be in the upper quintile groups of income. Furthermore, the richest quintile has an average income that is over 15 times larger than that of the poorest segment. Even the difference between the forth and fifth quintiles are large, the latter ones being 188% wealthier than the second best fifth in society in terms of income. Another important factor that can be apprehended from the table relates to the magnitude of the standard deviations. They can be considered small for the first four quintile groups. This suggests that within those groups, income *per adult equivalent* is fairly even. In other words, the vast majority of people within those groups have an equivalised income that is not far off the mean value of the group itself. The same cannot be said with regards to the last quintile. The standard deviation in this group is nearly as large as the mean, suggesting that the values for income are widely dispersed. That can be indeed observed in the later groups, namely the richest 10%, 5% and 1%. Whereas the mean grows rapidly in those segments, so do the standard deviations. Again, this suggests that there may exist few people with extremely large incomes. As an illustration, for this sample, the five richest people in the sample have an equivalised monthly income that ranges from R$ 31,819.10 to R$ 38,890.87, more than 10 times the mean of the richest quintile group. The percentage covered by private insurance in each group follows the same pattern, that is, in the lowest income groups a very small proportion of the population is covered, whereas in the higher groups, the majority has private health insurance.

Another important aspect of Brazilian society has to due with ethnicity. Even though the nation has never suffered from racial problems in the magnitude observed in the United States or South Africa, being a post-colonial slave intensive economy means that traditionally afro-descendants were worse off in several aspects of living when compared to their white counter parts. Table 4.2 presents some information regarding ethnicity in Brazil, as observed in the 2008 PNAD Survey.

Table 4.2 – Ethnic Differences

Ethnicity	% Population	Mean Income	Physician Visits
Mixed	47.01	725	65%
White	44.80	1378	70%
Black	7.32	747	67%
Asian	0.47	2103	70%
Native	0.32	746	64%
n/a	0.07	700	29%
Total		1,050	67%

Source: National Household Sample Survey (PNAD), Health Supplement, 2008.
Note: Income in local currency of 2008.

The first interesting aspect demonstrated in the table has to do with the percentage of people under each category. Nearly half the population is mixed raced, which in this context means black mixed with some other race (most frequently white, but not necessarily so). The second most prevalent race is white, for which the mean equivalised income is much higher than for all other, with the exception of Asian. This latter, on their turn, appear to have the highest income *per equivalent adult*, when considering the race spectrum, although they consist of a particularly small group of people in the country (less than 0.5%), and possess a relatively large standard deviation, indicating that income is not concentrated around the mean for this group. Asians came to Brazil in several immigration waves in the 19th and early 20th centuries, and have developed thriving communities due to their discipline and commitment to education. The Asian population in Brazil is mostly concentrated in the South-East region, and São Paulo is the city with the larger concentration of Japanese people (or their descendants) outside Japan. Finally, it is interesting to realise that the average income from native Brazilians (Indians that are legally protect under Brazilian civil law) have a higher mean income when compared to mixed race and nearly the same as black. This could be because, generally, native Brazilians live in isolated communities, are not integrated to civil society and live mostly on income transference programmes funded either by the government or NGOs. Together, black and mixed raced account for 54.33% of the population, and consist of the lower income segments as can be seen directly from the table. They also visit the doctor less than white or Asians.

Another important aspect of Brazil has to due with education. As in many developing nations, the country is not yet very educated. Tables 4.3 (a) and (b) show equivalised income and self-assessed health per educational level respectively.

Table 4.3 - Education

(a) Equivalised *per capita* income by level of educational achievement; and

Educational Achievement	**Mean**	**Sd**
Undetermined	203	202.34
No education (0 years)	187	279.42
Primary (1 - 8 years)	283	414.99
Secondary (9 - 11 years)	418	626.96
Higher (15+ years)	1,328	1697.76
Total	332	632.06

(b) SAH by level of educational achievement

Self-Assessed Health (%)	**Educational Achievement**				
	No education	Primary	Secondary	Higher	Mean
Very Good	23.53	19.78	25.32	35.73	23.14
Good	49.06	52.94	58.59	54.16	54.0
Regular	20.95	22.56	14.67	9.59	19.04
Bad	5.39	3.79	1.28	0.35	3.07
Very Bad	1.07	0.93	0.14	0.17	0.75

Source: National Household Sample Survey (PNAD), Health Supplement, 2008.
Note: Number of observations: n = 34624.

Even though education achievement is still fairly low in the nation, a positive association between income and education seems to exist. A person who has completed secondary education (A-level equivalent), on an average has an income in 50% higher than an individual with complete primary. And a university degree means one is likely to earn 6 times more, when compared to complete primary, or three times as much, in comparison with the complete secondary counterparts. In terms of health, one also sees a positive association, i.e. more educated people are healthier, although this should be considered parsimoniously, as from the table, one cannot disentangle how much the positive association is indirectly linked to income (which is both positively associated to education and health).

4.5.2 Self-assessed Health: how healthy do Brazilians feel?

In this study, we have used self-assessed health as a predictor for health care need, due to its high predictive power of mortality and health care use (Idler and Benyamini, 1997, DeSalvo et al., 2005). Table 4.4 shows the distribution in percentile terms of self-assessed health by income quintile groups.

Table 4.4 – Self-Assessed Health by Income Quintile Group

Self-Assessed Health (%)	**Equivalized Household Income Quintile Groups** 1st Poorest	2nd 2nd poorest	3rd Middle	4th 2nd Richest	5th Richest	All
Very Good	18.81	19.33	20.29	23.45	32.64	23.07
Good	55.56	55.05	52.35	54.65	52.19	53.92
Regular	21.28	20.89	22.25	18.51	13.32	19.16
Bad	3.53	3.84	4.24	2.76	1.26	3.1
Very Bad	0.82	0.89	0.87	0.63	0.59	0.75

Source: National Household Sample Survey (PNAD), Health Supplement, 2008
Note: Number of observations: n = 38791.

The table also indicates that health is positively correlated with income, i.e. the richer a person is the more like he or she is to enjoy (particularly very) good health. That is in line with common knowledge and also findings across several studies both in the developed and developing world (Adler et al., 1993, Pritchett and Summers, 1996, Gravelle, 1998). Looking at the values more closely, one can also see that the main difference lies on people responding very good and regular. Whereas roughly 19 to 20% of people in the first three income quintiles groups of the population consider themselves to have very good health, more than 32% of the richest fifth of society believes to enjoy such health status. That accounts for a relative difference of more than 50%.

Although a positive gradient between income and self-assessed health exists, it does not appear to be very steep, at least in the lower half of the distribution. It is possible that this is partly due to reporting bias in self-assessed health. Self-assessed health is a proxy to health status that depends on the perception of the individual. In fact, although studies have shown self-assessed health to be a good proxy to health status on average (Idler and Benyamini, 1997, DeSalvo et al., 2005), there is evidence that poorer individuals are more likely to report good health than richer individuals despite having the same “objective” morbidity (Sen, 2002, Sen, 1998). Hence it is possible that reporting bias exists, masking the true slope between income and health status. However, it may be that the income gradient in health does indeed become steeper in the upper two quintile groups, and more prominently so in the highest income group. This is consistent with the findings of Campino et al (2001) in their report on inequalities in health and poverty for PAHO, though they also used self-reported health and the data used was not representative of the country.

In terms of the analysis of inequality in health care, to which we will turn our attention later in this chapter, the existence of a positive gradient between health status and income means that we will need to adjust the level of need we take into consideration. That is due to the fact that healthier people may have a diminished need for health care. At least in principle, as wealthier people are also healthier, their need for care should be smaller.

4.5.3 Chronic Conditions in Brazil: evidence of under diagnosis?

Traditionally in the health equity literature, one is interested in differences between groups - most commonly income groups - that can be considered unjust or unfair (O'Donnell et al., 2008, Van Doorslaer et al., 1997a, van Doorslaer et al., 2000, Devaux and De Looper, 2012, Gravelle, 1998, d’Uva et al., 2009). In that sense, it is a wide spread practice to adjust the measures of inequality for age, gender, self-assessed health and prevalence of chronic conditions. The basic idea is that the individuals who possess a greater need for health care should be entitled to receiving more care, and thus, so long as the use of care is need-driven, a certain degree of inequality is unproblematic.

The logic behind the adjustment in terms of age, gender and prevalence of chronic conditions is fairly simple. In general, women have a greater need for health care than men, which is particularly true if one considers reproductive and maternal care. The very young and the very old are more prone to developing health conditions due to the lack of immunity and their larger recovery time spans. And finally, an individual with any chronic condition needs frequent or constant care to maintain a good health status. And once sick, any illness is more serious and threatening due to the existence of comorbidities. All these facts were originally asserted by epidemiology and proved useful for the correct measurement of inequities in health and health care.

Nonetheless, the actual correctness of need adjustment factors depends on the shape of the need factors distribution in any sample or survey. If one believes the data not to reflect reality, one might consider problematic correcting for (incorrect) need factors. Indeed, we believe this is the case for the prevalence of chronic conditions in Brazil, based upon the data from PNAD 2008. Figure 4.1 presents the prevalence of 12 chronic conditions, namely a) arthritis, b) asthma, c) back problems, d) cancer, e) cirrhosis, f) depression, g) diabetes, h) heart disease, i) hypertension, j) renal failure, k) tuberculosis and l) tendinitis, by income quintile group.

As we have mentioned before, it is a widely accepted fact that wealthier members of society are also healthier. The descriptive statistics of self-assessed health previously pointed to the exact same direction (see Table 4.4). Following the same pattern, one could expect the richer quintiles to have a lower prevalence of chronic conditions, once healthier individuals have such lower prevalence of bad and very bad health status.

However, the observation of the graphs tells us a different story.

Figure 4.1 – Prevalence of Chronic Conditions in Brazil

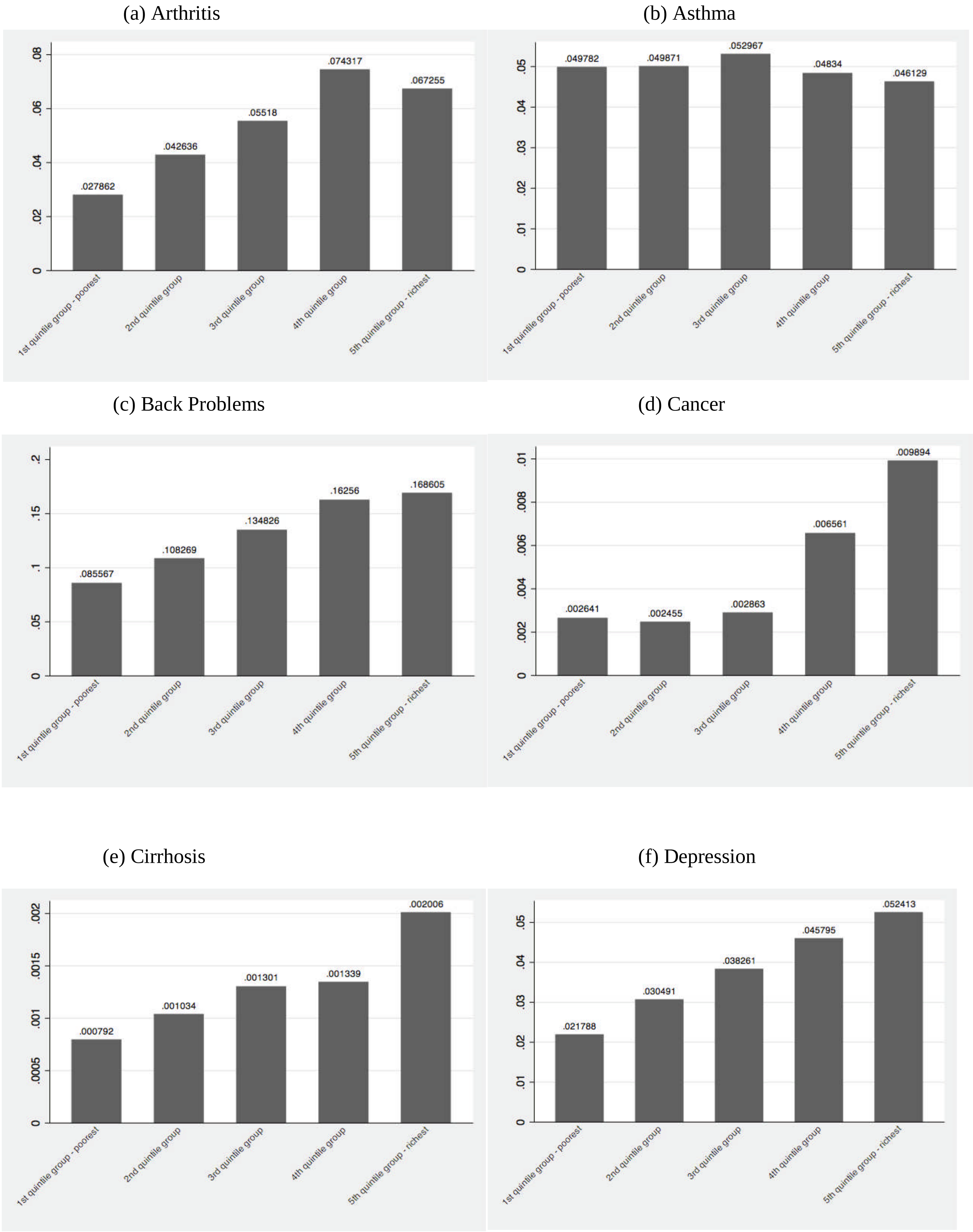
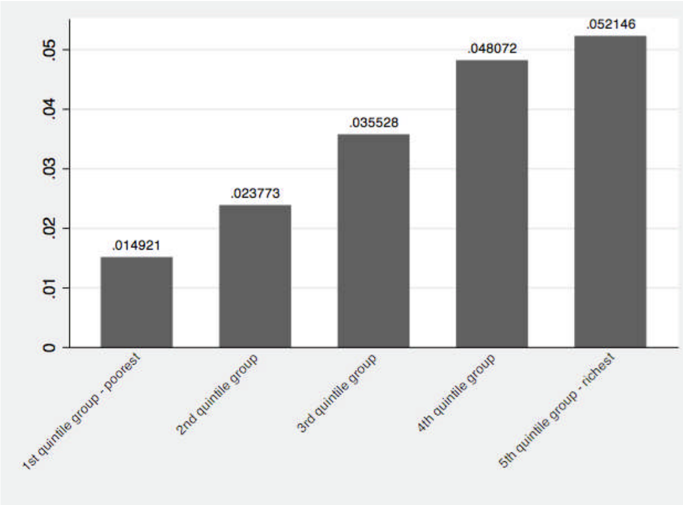
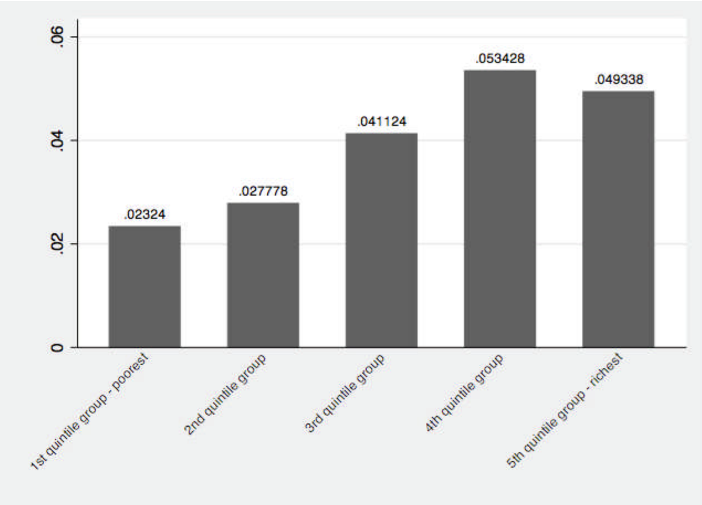


Figure 4.1 – Prevalence of Chronic Conditions in Brazil (Continued)

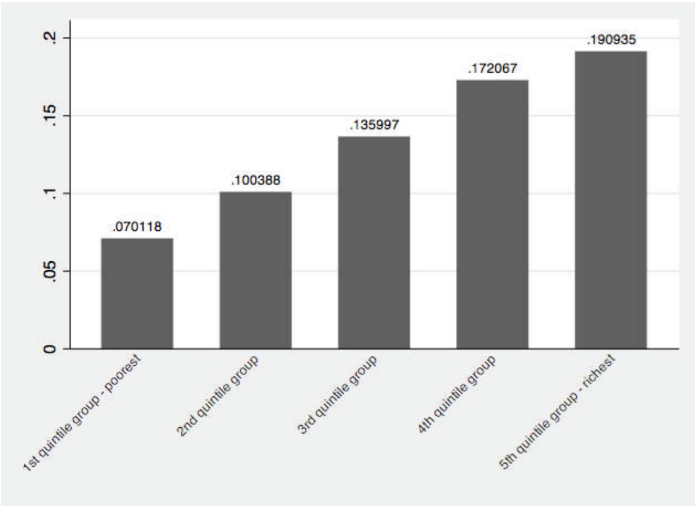
(g) Diabetes



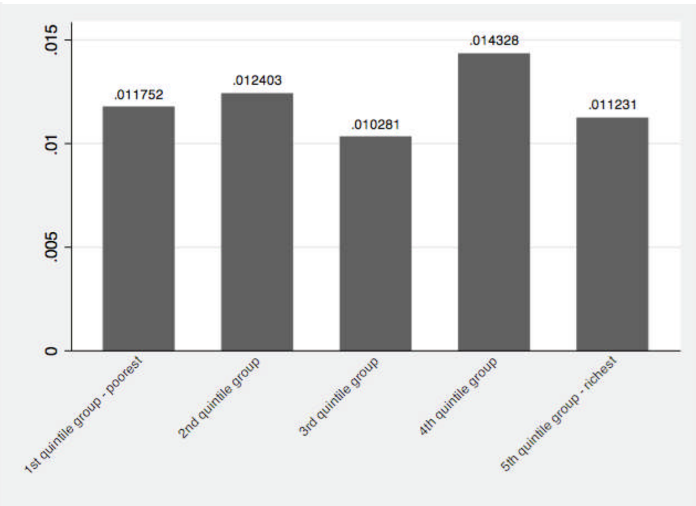
(h) Heart Disease



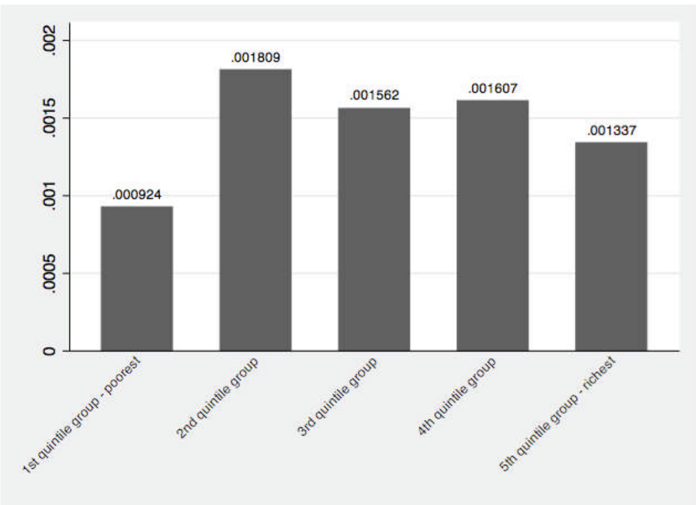
(i) Hypertension



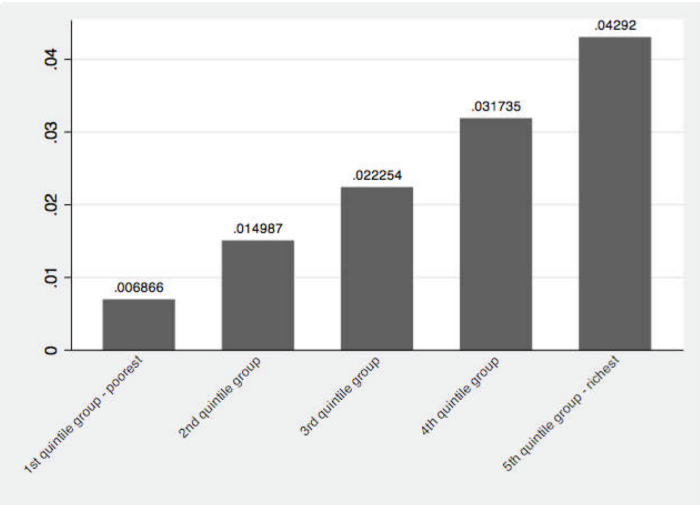
(j) Renal Failure



(k) Tuberculosis – TB



(l) Tendinitis



Source: National Household Sample Survey (PNAD), Health Supplement, 2008.

In practically none of the 12 graphs can we observe the expected behaviour, i.e. a downward slope in prevalence as we move along the income distribution. The exception may be asthma, where prevalence is relatively stable throughout the first three quintiles and mildly downward sloping in the latter two. The other 11 conditions can be divided into three groups, in accordance to the shape of the distribution.

The first group includes seven of the remaining eleven conditions (back problems, cancer, cirrhosis, depression, diabetes, hypertension and tendinitis). In this group a clear crescent path can be seen in the distribution, unreasonably suggesting that the richer an individual is, the more like he or she is to have one of these comorbidities. Within this group, the case of cancer is particularly interesting, as the behaviour of prevalence seems somewhat exponential, that is, moving towards the richer segments of society exponentially increases the likelihood of getting cancer.

The second group of distributions includes arthritis and heart disease. In these two conditions, a crescent slope exists until the fourth quintile, after which the slope is reverted negatively (although not reaching the value of the middle quintile). The structural break in the distribution suggests that only the very rich produce the expected behaviour, even though there are no epidemiological, medical or even social reasons that can explain the reverse behaviour for quintile groups one to four.

The final and third group is the most difficult to explain and includes renal failure and TB. In this group no straightforward pattern can be observed in the distribution. Particularly the case of TB is puzzling. In the medical literature, tuberculosis is strongly associated with malnutrition and overcrowding, having TB even been considered one of the principal *diseases of poverty* (Lawn & Zumla, 2011). Hence one would expect a steep negative slope or at least a much larger prevalence of the disease amongst the poor, represented in the first quintile. The exact opposite is true, as the poorest quintile has the lowest value of them all.

Although different social patterns exist among different conditions, one hypothesis seems appropriate to all cases: that chronic conditions are under diagnosed in the poorer segments of society. The hypothesis of under diagnosis is also strengthened by the format of the question relating to chronic conditions. The question explicitly asks: “Have you ever been diagnosed by health care professional with ___________?” (IBGE, 2008). In fact, the wording of the survey question seems important. Considering its focus on diagnosis, the patterns of the graphs in Figure 4.1 are plausible in the case where the poor are less likely to access and receive medical attention, which implies they are less likely to be diagnosed by a health care professional. Thus, one could speculate that the patterns presented in the graphs translate into evidence of income-related inequality in being diagnosed with a chronic condition. Although inequality in the prevalence of chronic conditions in

Brazil is not investigated further in the scope of this thesis, the inclusion of such variables as a measure of need for health care could potentially bias the measure of overall unfair inequality.

If under diagnosis exists, simply adjusting our estimates for chronic conditions would result in an underestimation of the existing inequality. This is simply due to the fact that such adjustment would imply that the wealthier are sicker, thus, need more care and are entitled to have so, which is neither true nor correct. The existence of under diagnosis in Brazil might be an important reality from a policy-making perspective. And it goes to prove that adequate descriptive statistics is not only a starting point, but may point out interesting and relevant analytical findings.

4.6 Results

The results for both the bivariate analysis and the multivariate approach required as a first step standardising logistic regressions. The basic model regressed physician visits on age, sex, self-assessed health and income on log scale. The intermediate model included region, education and ethnicity as covariates, as well as the variables of the basic model. Finally, the comprehensive model also incorporated urban/rural status, employment status, family type, coverage by health insurance and the seat-belt variable as a proxy for health care treatment preferences. Table 4.5 presents the marginal effects and standard errors of the logit regressions for each of the three models.

The coefficients all have plausible signs and, as expected, the size of the income coefficient decreases as more social variables are included in the models. Our base case model reported below does not include any interaction terms. 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. Interaction terms are important from a theoretical perspective, however, since they are the main source of differences between the fairness gap and direct unfairness. If the estimation model of direct unfairness and the fairness gap had interactions, or indeed if they are estimated in a non-linear fashion, as they are in this thesis, the rankings produced by such variables would be different. Thus, one can expect the results in terms of inequality to differ.

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. This later derived from the fact that the number of individuals who don't ride in the front seat is fairly small, and this may not reflect their risk perception, but other cultural characteristics. 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.

Table 4.5 –Standardising Regressions – Marginal Effects and Standard Errors

	Basic		Intermediate		Comprehensive	
	mg eff	**se**	**mg eff**	**se**	**mg eff**	**se**
ln(income)	0.067	0.003	0.044	0.004	0.016	0.004
Male (base)						
Female	0.180	0.004	0.174	0.004	0.173	0.004
Age group (base: younger than 15 years of age)						
15 - 29	-0.086	0.009	-0.031	0.009	-0.029	0.007
30 - 44	-0.020	0.009	0.041	0.009	0.011	0.007
45 - 60	0.005	0.009	0.074	0.010	0.025	0.006
60 +	0.046	0.012	0.121	0.012	0.073	0.007
Self-Assessed Health (base: Very Good Health)						
Good	0.062	0.006	0.070	0.004	0.077	0.007
Regular	0.215	0.004	0.230	0.006	0.240	0.004
Bad	0.322	0.006	0.339	0.010	0.348	0.006
Very Bad	0.310	0.010	0.325	0.022	0.352	0.010
Educational Achievement (base: no education)						
Primary			0.044	0.005	0.009	0.009
Secondary			0.091	0.009	0.041	0.005
Higher			0.136	0.011	0.062	0.010
Undetermined			0.120	0.006	0.099	0.011
Region (base: North)						
North East			0.039	0.005	0.022	0.009
South East			0.084	0.005	0.054	0.005
South			0.046	0.007	0.026	0.005
Centre West			0.041	0.007	0.022	0.008
Ethnicity (base: white)						
Native			-0.033	0.004	-0.041	0.063
Black			-0.005	0.051	-0.006	0.004
Asian			0.007	0.004	0.003	0.004
Mixed			-0.024	0.010	-0.034	0.092
Urban (base)						
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		0.0937		0.1153
Number of observations		34624		34624		28067

4.6.1 Variance as a measure of unfair inequality

Previously, when authors tried to calculate unfair inequality applying the concepts of direct unfairness and the fairness gap, they have reported variances as measures of inequality (García‑Gómez et al., 2014, Jusot et al., 2013). Table 4.6 presents the variances calculated for each model using both direct unfairness and the fairness gap.

Table 4.6 – Variance as a measure of inequality - Direct Unfairness and Fairness Gap

	Models		
	Basic	*Intermediate*	*Comprehensive*
Direct Unfairness	0.004888	0.008831	0.013048
Fairness Gap	0.004888	0.008928	0.013375

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

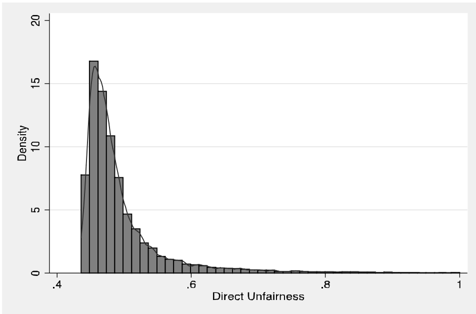
As more variables are included in the model, i.e. as we move from the basic to the intermediate and then, the comprehensive model, the variances of both direct unfairness and the fairness gap measures increase. This is also a mathematical inevitability in our case, since as we transition model specifications, a greater number of covariates are included. And the greater the number of covariates, the greater statistical degrees of freedom there are for the "explanatory" variables to fit the data. This sensitivity of the measure to the model specification is arguably appropriate, as models with a greater number of unfair variables also potentially have a greater degree of unfairness in the overall measure. However, if only one more comprehensive model were estimated, but with different covariates considered "fair" and "unfair" in sensitivity analysis, as suggested by Fleurbaey and Schokkaert (2009), the observed sensitivity would not be unequivocal, it would depend on the contribution of each factor to inequality.

Nonetheless, the high sensitivity of the variance to differences in data availability and methodological choices about model specification could potentially hamper comparisons between studies and settings. Furthermore, the variances are mean dependent measures of inequality, which could be hard to interpret and not very informative in terms of the magnitude of the inequality when comparing different settings or procedures. The distributions of direct unfairness and the fairness gap are presented below in Figures 4.2 (a) and (b).

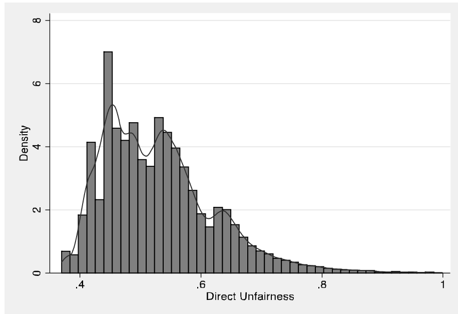
Figure 4.2 –Distributions of Direct Unfairness and the Fairness Gap across the population

(a) Direct Unfairness

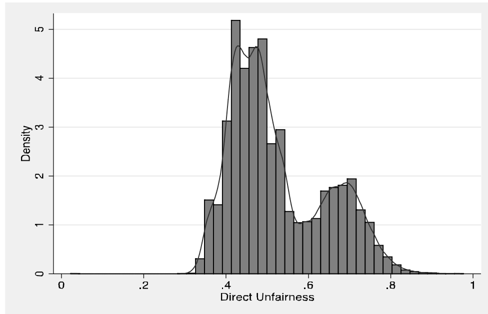
Basic



Intermediate

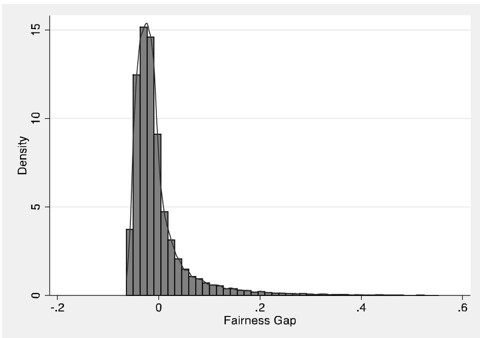


Comprehensive

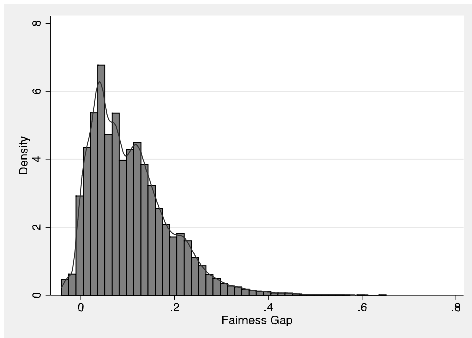


(b) Fairness Gap

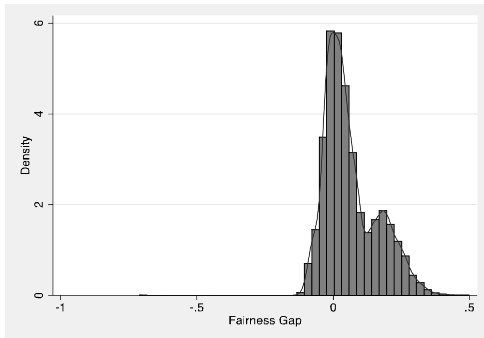
Basic



Intermediate



Comprehensive



Source: Data from the National Household Sample Survey (PNAD), Health Supplement, 2008

Figures 4.2 illustrate that including more variables in the models results in differently-shaped distributions: whereas the basic model has a distribution highly centred around the mean but with a long right-sided tail (common in income distributions), the comprehensive model has a more spread out distribution, where the right tail, although still in place, is more balanced. The distribution for the comprehensive model is clearly bimodal. This is the result of including "insurance status" in the model as an "unfair" source of inequality: this binary variable has a strong influence on the predicted probability of visiting the doctor. As expected, given that our model does not contain interaction terms, the fairness gap distributions are very similar to those of direct unfairness. The main difference between the distributions is that the mean value of DU sits at around 0.5, for FG it is about zero, as a consequence of the diverging approaches. Direct unfairness creates an artificial distribution where fair sources of inequality do not play any role, while the fairness gap corrects the observed distribution of latent health care by subtracting out the distribution of appropriate health care based on fair determinants of inequality.

One interesting feature of using the variance as a measure of inequality is the possibility of decomposition, so one may look at factors contributing to inequality. Table 4.7 decomposes the variance of direct unfairness and the fairness gap to examine the contribution of different unfair determinants of health care to overall inequity.

Table 4.7 – Decomposition of Variance – Direct Unfairness and Fairness Gap

Percentage contribution to inequality

	DIRECT UNFAIRNESS	FAIRNESS GAP
	Basic	
Income	94.86%	94.83%
Residual	5.14%	5.16%
Total	100.00%	100.00%
		Intermediate
Ethnicity	0.68%	1.22%
Education	16.17%	17.51%
Region	17.34%	18.14%
Income	59.13%	55. 21%
Residual	6.68%	7.92%
Total		100.00%
	Comprehensive	
Employment Status	0.21%	0.22%
Ethnicity	0.28%	0.55%
Education	1.08%	1.08%
Region	1.78%	1.98%
Family Type	2.69%	2.91%
Urban Status	4.78%	5.91%
Income	4.83%	4.78%
Health Insurance	79.62%	77.50%
Residual	4.73%	5.07%
Total	100.00%	100.00%

Source: National Household Sample Survey (PNAD), Health Supplement, 2008.

Here again there is not much difference between the drivers of inequality in direct unfairness and the fairness gap, when decomposing the variance. It is, however, noticeable that by adding covariates, income becomes less and less important. Finally, in the comprehensive model health insurance seems to be the main driver of inequality, accounting for more than ¾ of the unfair variation. The fact that private health insurance is the main component of inequality, as shown in Table 4.7, must be considered carefully. As mentioned previously, private health insurance in Brazil can be directly purchased by individual or can be a benefit of employment. In the first case, a direct correlation between private health insurance exists. In the second case, it can be argued that better employment guarantees private health insurance coverage, so if one considers that better employment also means higher income, an indirect relationship between private health insurance and income also exists.

4.6.2 Income-related inequality versus unfair overall inequality

Following our analysis, given that we were not particularly happy with the variance as a measure of inequality due to its difficulty in comparability, we now turn to our proposed measure of overall unfair inequality. Our innovation relies on the computation of the Health Care Advantage Rank (HCA Rank), and the use of the standard bivariate indices. Following their mathematical definitions, stated in equations 3 and 4, HCA rank used direct unfairness for the calculation of the standard and Erreygers modified Concentration Index. In the case of the Horizontal Inequality index, the rank was created based on an individual's position in terms of the fairness gap. Table 4.8 displays our proposed measure of unfair overall inequity 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 overall inequality.

Table 4.8 – Unfair Overall inequity *vs* Income-related Inequity

	Basic		**Intermediate**		**Comprehensive**	
	Income-related	*Unfair Overall*	*Income-related*	*Unfair Overall*	*Income-related*	*Unfair Overall*
CI	0.0541	0.0543	0.0501	0.0610	0.0478	0.0702
HI	0.0504	0.0539	0.0574	0.0758	0.0581	0.0852
Erreygers CI	0.1424	0.1425	0.1319	0.1634	0.1284	0.1884

Source: National Household Sample Survey (PNAD), Health Supplement, 2008.

Notes: 1) HI = $CI_{observed} - CI_{predicted}$

2) $CI_{observed}$ measured on a latent scale

3) Erreygers CI = 4*μ*CI"

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. That is due to the fact that 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 other cases, however, the unfair overall indices are substantially larger than their income-related counterparts; with the largest indices found in the most comprehensive model that incorporates the most dimensions of unfair inequality. The intermediate model considers four sources of unfair inequality (income, educational achievement, ethnicity and region), whereas the comprehensive model considers nine (income, educational achievement, region, ethnicity, employment status, an urban/rural status, family type, health insurance coverage and behaviour towards health care). It is not surprising that the measure of overall inequality incorporating these nine sources of unfair inequality is larger than that of income-related inequality, focusing on just the one source of unfair inequality. It is also interesting to observe that whereas adding covariates to the analysis of income-related inequality decreases the standard and Erreygers concentration indices, the opposite happens in the case of unfair overall inequality. This may be attributed to the neutral status of the covariates in income-related inequality measures of inequality and the fact that adding them to the model eliminates variation due to them, once they are controlled for.

As before, it is desirable to understand how far income and all the other social variables contribute to unfair overall health care inequity. Table 4.9 presents the decomposition of unfair overall inequality using the standard concentration index (CI). As well as the elasticities and individual CIs, it presents the contribution (and percentage contribution) of each factor towards the total CI. 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 intermediate model, income and education are the most important factors, and appear to have roughly the same magnitude. 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. This is consistent with the decomposition of variance performed above. 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. Furthermore, income appears to be only slightly more important in terms of inequality contribution than education and treatment preference proxied in the seat belt variable, which can also be interpreted as a suggestion that this variable indeed picks up treatment preference behaviour.

Table 4.9 – Decomposition of the Unfair Overall Inequality using CI

	Contribution	Percentage Contribution
Basic		
Income	0.02907	53.56%
Residual	0.02521	46.44%
Total	0.05428	100.00%
Intermediate		
	Contribution	Percentage Contribution
Ethnicity	0.00014	0.23%
Region	0.00424	6.95%
Education	0.01596	26.18%
Income	0.01798	29.50%
Residual	0.02264	37.14%
Total	0.06096	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%

Source: National Household Sample Survey (PNAD), Health Supplement, 2008.

4.7 Conclusion

The measurement of equity in health care remains dominated by a bivariate approach that focuses only on one source of unfair inequality in health care at a time – typically income. This paper develops a new approach that allows simultaneously for multiple sources of unfair inequality, drawing on theoretical work by Fleurbaey and Schokkaert (2009, 2011) and augmenting existing applications by introducing a new form of ranking that allows for the measurement of overall inequity in health and health care. This was achieved by using the multivariate framework measures *direct unfairness* and the *fairness gap*, as proposed by FS, ranking individuals according to their position in terms of Health Care Advantage (HCA) and subsequently applying the standard apparatus of the bivariate approach: the concentration index and decomposition thereof. The proposed HCA approach of unfair overall inequity in health care has the advantage of being fairly simple to interpret, as well as facilitating decomposition. Our approach is a general framework for measuring unfair inequality, in which income-related inequality or socio-economic-related inequality are only a particular case. As to the case of Brazil, one can conclude that overall inequity is much larger than income-related inequity, and that the possession of health insurance and residing in urban areas are the most important factors contributing to that inequality – more important than income.

Income-related inequality in health care in Brazil had been previously measured (Macinko and Lima-Costa, 2012, Almeida et al., 2013). Both studies found a concentration indices smaller in magnitude: 0.033 and 0.0429 respectively. We believe this to derive from their adjustment for chronic conditions. As we have shown, 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.

The current study has a number of limitations. Firstly, although by choosing not to use chronic conditions as predictors for health care need we may have avoided a potential reporting bias, we understand that the true estimate of overall unfair inequality depends on the correct prediction of health care use based on need. Secondly, and perhaps more importantly, drifting from the current inequality of opportunity developments, our study does not rely upon structural modelling, nor does it allow for the inference of causality. This means we can identify contributors to overall inequality, but not its cause. Finally, there are limitations in terms of the data used, as is often the case in developing countries.

As to the main contributions of this paper, we first highlight our innovative health care advantage rank relies on the measurement of direct unfairness and the fairness gap, which in turn bear close similarities with direct and indirect standardization. This new approach allows for multiple normative positions, both when considering which variables to include in the fair and unfair vectors, as well as regarding the index chosen for reporting the measure of inequality. Secondly, this is the first time that to our knowledge the multivariate framework as proposed by FS was applied to health care in a developing country. Finally, by observing unfair overall inequality instead of income-related inequality we are producing policy relevant information, in particular to potential areas of investment. Further investigations could, for example, explore whether the importance of urban status is related to the supply of health care in rural areas or if there is evidence of moral hazard for people covered by health insurance, given that this is the most important driver of inequality.

Future research could also investigate the matter of under diagnosis, by applying the Health Care Advantage approach using chronic conditions as outcome variables, or measures of health. Another interesting avenue for future research would be exploring the applications of the HCA approach, with special interest to resource allocation within the health system.

Chapter 5: Overall inequity in preventive healthcare for women in Brazil

Abstract

This study aimed to analyse overall inequity in the use of two important forms of preventive healthcare for women in Brazil – mammography and cervical screening. We measured overall inequity using multiple social variables that may be considered to represent potentially unfair sources of inequality in healthcare utilisation, and then decomposed this to examine the relative contribution of each social variable to overall inequity. We used the Health Supplement of the National Household Sample Survey for the year 2008, which includes 110,280 women aged 15+. To compute the measure of overall inequality we have ranked individuals according to their position in the Health Care Advantage Rank, and have compared this measures to the traditional income-related inequality apparatus. As expected, we found that overall inequity was substantially larger than income-related inequity both in mammography and cervical screening. For cervical screening, the Erreygers concentration index for overall inequity was 0.41, for the model that included several potentially unfair sources of inequality, compared with an income-related Erreygers concentration index of 0.19, and comparable figures for mammography were 0.35 and 0.25. The main components of overall inequity were as follows (with proportional contribution in brackets for mammography and cervical screening, respectively): health insurance (44.7%, 78.8%), income (14.5%, 4.4%), medical treatment preferences (11.8%, 0.8%), region (11.4%, 3.1%), education (7.9%, 3.3%) and family type (5.6%, 3.7%).

5.1 Introduction

This study seeks to analyse unfair inequality in the use of two important forms of preventive care for women in Brazil – mammography and cervical screening. Preventing cancer-related mortality and morbidity among women not only improves population health but also potentially contributes to economic development in low and middle-income countries like Brazil. This is especially true now that women are becoming an integral part of the labour force in Brazil, and thus contributing directly to economic growth statistics, as well as providing unpaid informal household production services which contribute to economic development in a less visible way. In the past 30 years, women have gained relevance in the Brazilian labour market, so much so that the number of women economically active has grown from 14.6% in 1970 to 42.8% in 2012, nearly a three-fold increase (IBGE, 2012).

We aim to measure overall inequity in preventive care, including inequality related to multiple social dimensions of inequality, instead of merely focusing on income-related inequality. As in the previous chapter, we rely on the multivariate framework proposed by Fleurbaey and Schokkaert (Fleurbaey and Schokkaert, 2009) to compute individual measures of *direct unfairness* and the *fairness gap*. This approach measures the overall degree of unfair inequality in healthcare utilization, and then decomposes this to examine the relative contribution of multiple social variables of concern to policy makers from an equity perspective. It is accepted in the literature that not every kind of inequality in health care is unfair, and that it is appropriate for people with different needs and preference for medical treatments to receive different amounts and types of care. When computing overall inequity measures, we use the Health Care Advantage Rank (HCA Rank), as proposed in the previous chapter. Like before, we report the measures of income-related and overall unfair inequality in three ways: the standard directly-standardised concentration index, the horizontal inequity index and the Erreygers modified concentration index. We used the Health Supplement of the National Household Sample Survey for the year 2008, which includes 110,280 women aged 15 and over (IBGE, 2008).

The choice of including all eligible women (aged 15 or older) can be justified by three distinct reasons. First, cervical cancer is most often (more than 90% of cases) a result of HPV infection (Bosch et al., 1995), which in turn is more likely to happen in sexually active women who have unsafe sex, and potentially multiple partners. Thus, it has been argued that the most "at risk" group are younger women. Acknowledging this fact, the current European Guideline for Quality Assurance in Cervical Cancer Screening recommends women to be screened from the age of 20 and highlights the importance of immunization against HPV on young women before becoming sexually active (Arbyn et al., 2010) Unfortunately, Brazil is a paternalistic catholic country, and this is reflected in policy-making. The target group of the policy regarding cervical screening (25 - 59) indirectly implies that the most "at risk" group of women are between 25 and 59. In terms of inequality measurement, had I focused the analysis on the policy-targeted group only I would potentially be (a) neglecting the possible inequality existing in an important group of women (younger than 25) and (b) implicitly agreeing with a sexist perception of healthcare need. Second, with regards to mammography screening, clinical studies show that women are most likely to develop breast cancer in their late 40s and 50s, as many types of breast cancer are linked to menopause (McPherson et al., 2000, Kelsey et al., 1993). However, other studies also show that women who develop breast cancer before the age of 40 often have a more aggressive and dangerous type of cancer, which could be argued is a different underlying risk (Paffenbarger Jr et al., 1980). The Brazilian Breast Cancer Screening Policy has changed over time, as a result of disagreement from the Brazilian Oncology Society with regards to the "targeted age group" from mammography screening, so much so that the policy changed in 2013. Whereas before 2013, women aged 40-49 were recommended for screening every 3 years, and 50-69 every year, after 2013 the periodicity was left to the discretion of the clinician for all women, with a maximum of 3 years. Once again, had my analysis focused on the targeted group only, I would potentially be neglecting the inequality existing in an important group of women. Third, in the thesis, due to the lack of causal inference, I do not explicitly evaluate the policies on cervical screening (which targets women aged 25 to 59) or mammography screening (targeting women aged 40 to 69). In fact, one of aims of this Chapter is comparing the measures of overall unfair inequality in two forms of preventive care that are different in nature, once mammography screening is capital-intensive and cervical screening labour-intensive.

For the purposes of this study, covariates include age, equivalised household income, using a square root scale, region, educational achievement, urban/rural status, family type, private health care coverage and preferences related to medical care. We have explicitly chosen not to use self-assessed health as a measure of health care need in the standardising regressions for two reasons: (a) given that in this paper we are looking at preventive care for women, and in terms of prevention, individuals possess equal need; and (b) we have run the standardising regressions including self-assessed health, but they were found to be statistically insignificant for the basic and comprehensive model specifications in cervical screening, and in the comprehensive models for mammography.

Previous literature has evaluated income-related inequality in some forms of preventive care in Brazil and has found it to be larger than inequality in curative care (Suárez-Berenguela, 2000, Rossi et al., 2009). Studies that focused on mammography and cervical screening in developed nations have also found inequality to exist (Moser et al., 2009, Lorant et al., 2002), although comparability of magnitude of inequality is not always possible, due to the choice of reporting (Couture et al., 2008, Palencia et al., 2010). The main contribution of the present chapter is going beyond income-related inequality and assessing overall unfair inequality in two interesting forms of health care. Inequalities in mammography and cervical screening might be indicative of wider inequality in the care for women and, due to their preventive nature, may implicate in the avoidance of women leaving the labour market due to illness.

After this introduction, the text is divided in methods, including a brief description of the proposed ranking, data and descriptive statistics, results and discussion and final considerations.

5.2 Methods

A number of different views regarding what is fair and unfair in terms of inequality in health care use exist. Essentially in income-related inequality, one considers variation in health care use that are due to income unfair, whereas variations derived from need factors such as age to be fair. All other variables included in the models are deemed neutral, once they are simply standardised for. In the case of overall inequality, the logic is somewhat different. Two main vectors exist, one including unfair sources of inequality in health care utilisation and one containing fair sources of variation. This allows for multiple normative positions, given that different researchers and policy makers may have different opinions regarding which vector to place a certain variable.

Unlike the previous chapter, for the current analysis in order to calculate income-related and overall unfair inequality, we have used only two different standardising models. The first one, the basic model, is our starting point. In this model, the measures of overall unfair and income-related inequality in health care are the same, as the only unfair variable taken into consideration is income. Finally, the comprehensive model is the best possible model specification and includes several variables that may contribute to explaining inequalities in women's care.

Besides education, ethnicity and region, the comprehensive model includes employment status, urban/rural status, family type, health plan coverage and health care treatment preferences, proxied by the use of seat belt, as it represents an approximation of the individual's behaviour towards risk, mostly the risk in driving and riding a car. In both model specifications, the variable age is used as an indicator of need. Furthermore, the variable seat belt use is considered fair, as it denotes treatment preferences.

5.2.1 Overall unfair inequality in preventive care for women: an application of the Health Care Advantage Rank

When looking at overall unfair inequality, Fleurbaey and Schokkaert have proposed two individual measures, namely i) direct unfairness and ii) the fairness gap. According to FS, direct unfairness eliminates the fair sources of inequality by setting them at reference values and predicting the outcome, in here the use of preventive health care services, based on unfair determinants only, while the fairness gap satisfies the egalitarian equivalence principle and provides a normative prediction of the health care this individual ideally should receive.

Recent literature on equality of opportunity has used a similar "fairness gap" approach, using the variance as a measure of inequality (García‐Gómez et al., 2014, Jusot et al., 2013). As we have pointed out in the previous chapter, although the variance has the advantage of being decomposable, it is an absolute measure of inequality that is sensitive to the mean. Thus, it is not possible to directly compare inequality in different forms of health care utilisation using the variance if such forms have different means, as is the case with mammography and cervical screening in Brazil. Furthermore, academics, policy advisers and policy makers are not used to looking at inequality using the variance, as the most common measure reported in the health literature is the concentration index, which due to familiarity may be considered easier to understand and use. One of the objectives of this Chapter is to compare inequality measures in both forms of preventive care, considering that it may useful for public policy thinkers, given that mammography is capital intensive, whilst cervical screening is labour intensive.

Therefore, we have, once again, chosen to apply the ranking modification proposed in the previous chapter, which allows for use of traditional apparatus of concentration and concentration ratio turns - the equivalent of the Gini index in the bivariate case - while at the same time incorporating measures of direct unfairness (DU) and the fairness gap (FG) as described by Fleurbaey and Schokkaert.

In this paper, the direct unfairness measure is used to create a ranking of the individuals, since it creates an artificial distribution where all legitimate variation is neutralized. In a way, this creates a measure of advantage in terms of receiving care, since every need has been properly corrected. If unfair inequality exists, then the person of lower rank is one less likely to receive care when in need, due to his disadvantage derived from unfair sources of variation. By contrast, the best place in the ranking is of the person who has an unfair advantage in terms of likelihood to receive the care, given their level of need and treatment preferences. The latter has more access than (s)he actually needs, which expresses an unfair advantage with regards to receiving health care. This we have called the Health Care Advantage Rank (HCA Rank).

The Health Care Advantage Rank can be created either using direct unfairness or the fairness gap. Our choice of using direct unfairness derives from the fact that the same specification can be used for both the relative and the absolute cases, although in this chapter the focus will be comparing inequality in mammography and cervical screening in relative terms. As in previous chapters, mathematically, we have defined the individual measure of direct unfairness as:

$$hc_{i\_du} = hc_{i\_predicted}\,(N_{ref},\ P_{ref},\ SES_i,\ Z_i) \qquad [1]$$

where direct unfairness is the predicted probability of using healthcare holding needs (N) and medical preferences (P) at reference, but allowing socio-economic status (SES) and other unfair variables (Z) to vary. In this chapter, given that self-assessed health was not statistically significant to explain the variation in the use of mammography and cervical screening, and considering that both procedures referred to women only, a single variable was placed in the need vector: age, which was held at mean. Medical treatment preferences were proxied by the seatbelt variable and held at the category “always” given that this predicted higher use of care.

The calculation of the measure of overall unfair inequity follows the traditional suit used in socio-economic equity measures, but instead of plotting the outcome variable against a socio-economic ranking, we plot the cumulative proportion of care against the health care advantage rank, and then standardised both directly and indirectly to obtain the concentration index (CI) and the horizontal inequity index (HI), respectively. We also calculate the Erreygers modified concentration index, based on the directly standardised concentration index, due to its interesting properties. The proposed approach has the advantage of enabling other forms of reporting, and we illustrate this by also reporting of extreme groups gaps and ratios. Another advantage of working with the traditional concentration-index type measures of inequality is the possibility of decomposition. According O'Donnell et al: "the concentration in health index can be broken down into the contributions of individual factors [...], where each contribution is [...] the degree of lawlessness that factor"(O'Donnell et al., 2008).

5.3 Data and some descriptive statistics

In this study we have used data from the Health Supplement of the Brazilian National Household Sample Survey (PNAD) for the year 2008. Structurally, PNAD makes 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, so all discussions and conclusions are valid on a national and subnational context (IBGE, 2008). Considering the national guidelines regarding the provision of mammography screening and cervical screening (INCA, 2013, CONASS, 2011), the variables used were binaries of whether women had had the procedure in the past two and three years respectively. In Brazil, in order to undergo a mammography or cervical screening, women have to be referred to diagnostic services by a physician, which implies that previous access to the health care system is necessary beforehand.

General descriptive statistics for the variables used in the study are in Table 5.1 We also highlight some more detailed descriptive statistics relating to income and the use of preventive care by women in Table 5.2.

Table 5.1 – General Descriptive Statistics

	Mean
Age	31.9
Education	
No formal education	20.6%
Primary	44.7%
Secondary	24.8%
Higher	10.0%
Urban Residence	85.1%
Unemployment	7.3%
Ethnicity	
White	45.6%
Mixed	46.8%
Black	6.9%
Asian	0.4%
Native	0.3%
Private Health Insurance	25.2%
Had a mammography in the past 2 years	41.0%
Had cervical screening in the past 3 years	74.3%

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

Table 5.2 demonstrates that the distribution of income is disproportional amongst women. The 20% richer possess an income roughly 15 times larger than the 20% poorest. Even the difference between the upper quintiles is large, the latter being 3 times larger than the former. The table also shows a positive gradient between the use of care and income, i.e. the richer the woman, the more frequently she uses the service, for the cases of mammography and cervical screening. This pattern is more pronounced for mammography, which could be correlated to the capital-intensive nature of the procedure. The positive gradient in both cases is in line with findings in the literature, which state that high-income class women use both preventive exams more than their lower-income counterparts (Gravelle, 1998).

Table 5.2 – Mean income and frequency of women attending mammography and cervical screening per income quintile group

Income Group	Mammography	Cervical Screening	Mean Income
Q1 - Poorest 20%	29.3%	66.0%	189
Q2 - Second poorest 20%	32.5%	68.9%	404
Q3 - Middle 20%	37.0%	72.7%	630
Q4 - Second Richest 20%	40.4%	79.9%	994
Q5 - Richest 20%	62.7%	84.3%	2979
D10 - Richest 10%	67.4%	85.6%	4058
V20 - Richest 5%	68.7%	89.1%	5721
P100 - Richest 1%	71.4%	88.5%	10986
Mean	40.9%	74.4%	1039

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

5.4 Results

5.4.1 Standardising regressions and utilisation models

Tables 5.3 and 5.4 present the results of the utilisation models in terms of marginal effects for mammography and cervical screening respectively[11]. Due to the binary nature of the outcome variables, logistic regressions were used. Table 5.3 indicates some interesting facts. Firstly, the higher the income the greater the likelihood of getting a mammography, although as we move from the basic to the comprehensive model the importance of income becomes smaller. It is also interesting to observe the effect of age. The likelihood of doing the procedure increases as age increase, reaching its peak at 45-49, it then starts to decrease again. Regarding other variables, the table shows that women in the South East are better off, when looking at the mammography procedure. As expected, people in urban areas are more likely to be scanned. Regarding private health insurance coverage, women covered by health insurance are more likely to have a mammography with an absolute probability increase of 0.144, all other factors constant, when compared to their uninsured counterparts. This translates into being (slightly more than) twice as likely to receive this form of care, given that the probability of uninsured women to getting a mammography is only 0.138, all other factors constant. It is also interesting to see that mothers of young children (under 14) are less likely to be screened, whereas mothers of mothers of older children are more likely, when compared to women with no children, and that wearing a seatbelt

[11] Tables presenting the odds ratios and respective standard errors (SE) of standardizing regression can be found in Appendix B.

does seem to increase the likelihood of being screened; indicating that this variable indeed captures behaviour towards risk.

In turn, Table 5.4 presents the proposed models using cervical screening as the dependant variable. As in the case of mammography, income (in natural log scale) is a statistically significant determinant of utilisation. Yet again, as we move from the basic to the comprehensive model, its relative importance diminishes as other correlated factors come to the fore. The pattern in terms of age, however, is not the same. For cervical screening, women aged between 25 and 39 are the most likely to be screened. Most other coefficients follow the same pattern as in mammography screening, that is, more highly educated women are more likely to have cervical screening, in accordance with evidence found in other inequality studies (Marmot et al., 2008, Kawachi and Kennedy, 1999). Furthermore, ethnicity appears to be an issue for the case of cervical screening, as white females are more likely to be screened. As are insured, urban inhabitants and women who live in the South East. Risk behaviour also seems to be picked up by the seatbelt variable in this case, although it is smaller in magnitude.

The main difference can be seen in terms of employment. Meanwhile for mammography, employed women are more likely to get the procedure, the opposite is observed in cervical screening. Whilst it may be difficult to outline a consistent explanation for this pattern, it seems to point to the direction that women in employment have greater access or greater preference for mammography, or even that they regard this procedure as more important than unemployed women. At the same time, the opposite dynamic can be found with regards to cervical screening, which is perhaps regarded as less important or less preferred by employed women, when compared to their unemployed counterparts. Notwithstanding, it was beyond the scope of this thesis to investigate in more details differences in the relationship between employment and the use of preventative care by women.

Table 5.3 – Utilisation model for mammography – Marginal Effects and Standard Errors

from logistic regression

Unfair Variables:	**Basic Model** (Income Only)		**Comprehensive Model** (Several Unfair Variables)	
	mg effect	**se**	**mg effect**	**se**
ln(income)	0.1307	0.005	0.0619	0.007
Age group (base: younger than 25 years of age)				
25 - 39	0.069	0.010	0.065	0.013
40 - 49	0.186	0.011	0.200	0.014
50 - 59	0.121	0.013	0.151	0.011
60 +	0.041	0.013	0.010	0.001
Educational Achievement (base: no education)				
Primary			0.057	0.011
Secondary			0.078	0.015
Higher			0.111	0.016
Undetermined			0.062	0.008
Region (base: North)				
North East			0.031	0.009
Centre West			0.042	0.008
South			0.050	0.011
South East			0.101	0.012
Ethnicity (base: white)				
Native			-0.009	0.007
Black			-0.013	0.002
Mixed			-0.009	0.006
Asian			0.010	0.008
Urban (base)				
Rural			-0.063	0.005
Employment Status (base: occupied)				
Unoccupied			-0.037	0.004
Family Type (base: no children)				
children under 14			-0.014	0.004
children 14+			0.012	0.009
Health Insurance (base: No)				
Yes			0.144	0.006
Seatbelt Preference (base: Always)				
Doesn't ride in front seat			0.042	0.008
Often			-0.020	0.003
Sometimes			-0.027	0.003
Rarely			-0.034	0.005
Never			-0.030	0.004
Adjusted R-squared	0.085		0.137	
Number of observations	11028		9005	

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

Table 5.4 – Utilisation model for cervical screening – Marginal Effects and Standard Errors from logistic regression

Unfair Variables:	Basic Model (Income Only)		Comprehensive Model (Several Unfair Variables)	
	mg effect	**se**	**mg effect**	**se**
ln(income)	0.0936	0.005	0.0385	0.008
Age group (base: younger than 25 years of age)				
25 - 39	0.031	0.013	0.037	0.016
40 - 49	0.008	0.014	0.019	0.016
50 - 59	-0.083	0.015	-0.111	0.015
60 +	-0.230	0.022	-0.205	0.020
Educational Achievement (base: no education)				
Primary			0.093	0.009
Secondary			0.133	0.012
Higher			0.156	0.031
Undetermined			0.092	0.020
Region (base: North)				
North East			0.006	0.001
Centre West			0.014	0.002
South			0.014	0.003
South East			0.023	0.008
Ethnicity (base: white)				
Native			-0.086	0.007
Black			-0.070	0.019
Asian			-0.053	0.080
Mixed			-0.070	0.009
Urban (base)				
Rural			-0.012	0.005
Employment Status (base: occupied)				
Unoccupied			0.047	0.004
Family Type (base: no children)				
children under 14			-0.058	0.013
children 14+			0.007	0.011
Health Insurance (base: No)				
Yes			0.157	0.007
Seatbelt Preference (base: Always)				
Doesn't ride in front seat			0.038	0.006
Often			-0.018	0.003
Sometimes			-0.022	0.004
Rarely			-0.028	0.005
Never			-0.025	0.004
Adjusted R-squared	0.044		0.071	
Number of observations	11028		9005	

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

5.4.2 Concentration curves and inequity indices

The utilisation models are informative, but they do not express measures of income-related or overall unfair inequality regarding the use of health care. Thus, we turn to the traditional apparatus of concentration curves and inequity indices, which allow inequalities to be summarised in a standard format that allows comparison with the standard literature on income-related inequality. Figure 5.1 (a) and (b) presents the concentration curves for mammography screening using both income rank and health care advantage rank, respectively. Similarly, Figure 5.2 (a) and (b) does the same for cervical screening. As all curves are plotting cumulative proportion of observed utilisation against one of the two ranks, the different ranking does not seem to make much difference in the shape of the curves, although in both cases, the inequality appears larger when people are ranked in terms of their position in the HCA Rank, that is expected, as the latter provides a measure of overall unfair inequality, of which income is only one aspect.

Figure 5.1 – Mammography screening Concentration Curves

(a) Income Rank (b) Health Care Advantage Rank

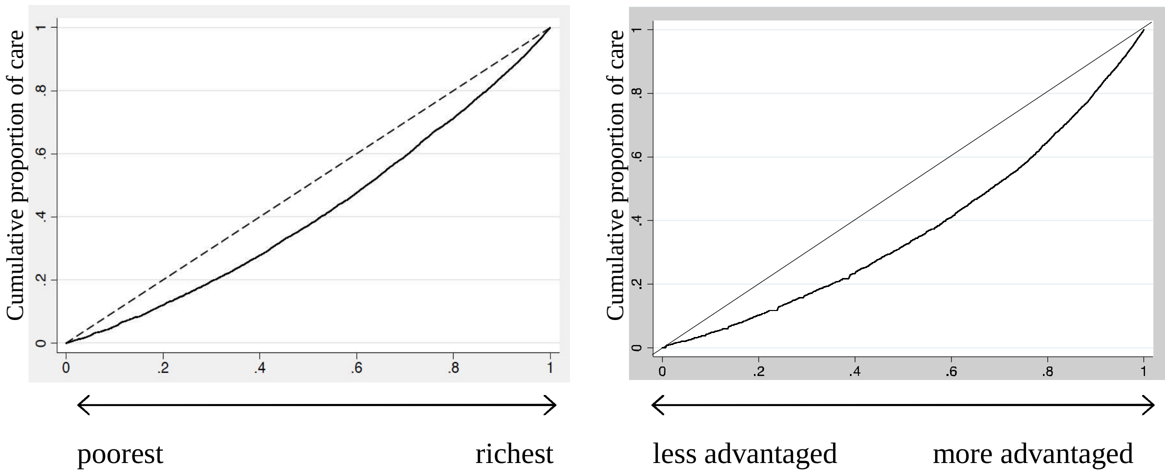
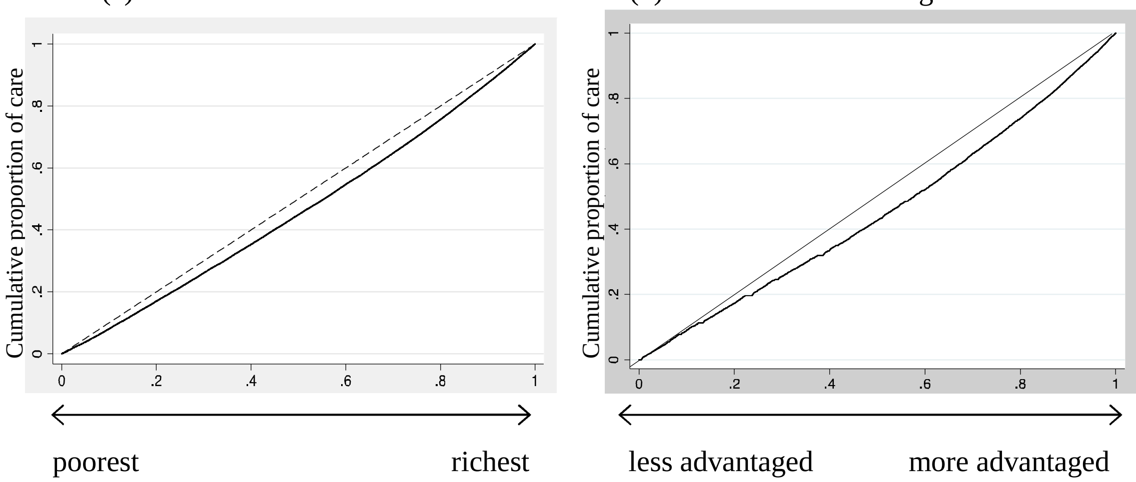


Figure 5.2 – Cervical Screening Concentration Curves

(a) Income Rank (b) Health Care Advantage Rank



From the Figures, inequality appears larger for mammography when compared to cervical screening, regardless of the ranking used. Indeed, even when comparing income-related inequality in mammography screening to overall inequality in cervical screening, the former seems to be larger. This is confirmed in the Concentration Indices (CI), displayed in Table 5.5.

The Table displays the standard directly-standardised concentration index (CI), the horizontal inequality index (HI) and the Erreygers corrected directly-standardised concentration index (Erreygers CI), calculated using each model for both outcome variables. It presents measures of income-related inequality in health care, calculated through the traditional bivariate approach, as well as in the overall unfair inequality, which uses the multivariate healthcare advantage approach.

For the basic model, as in the multivariate approach the only unfair variable is income, the results are the same results as the bivariate analysis (up until the third decimal place). This is because in this case the income rank and the healthcare advantage rank are identical, since the regression model predicts a positive monotonic relationship between income and healthcare utilization. However, with the inclusion of additional unfair variables, the multivariate indices become substantially larger than their bivariate counterparts. As mentioned before, the comprehensive model considers eight unfair variables (income, educational achievement, region, race, employment status, an urban/rural status, family type and health insurance coverage). Given that the latter model has more unfair sources of inequality, it is not surprising that the measure of overall unfair inequality incorporating these eight sources of unfair inequality is larger than that of income-related inequality.

The inclusion of covariates in the calculation of inequity indices in income-related inequality appears to do the opposite, i.e. the more variables included, the smaller the measure of inequality. This is a reflection of the neutral status of theses covariates. Once they are being controlled for, they no longer affect the measure of income-related inequality.

Table 5.5 - Income-related vs. Overall Inequality – selected Indices

	Basic		Comprehensive	
	Mammography			
	Income-related	*Overall*	*Income-related*	*Overall*
CI	0.1819	0.1822	0.1537	0.2133
HI	0.2146	0.2144	0.1647	0.2618
Erreygers CI	0.2983	0.2988	0.2521	0.3498
	Cervical Screening			
	Income-related	*Overall*	*Income-related*	*Overall*
CI	0.0778	0.0780	0.0659	0.1397
HI	0.0729	0.0737	0.0652	0.1577
Erreygers CI	0.2303	0.2310	0.1952	0.4134

Source: National Household Sample Survey (PNAD), Health Supplement, 2008
Notes: 1) CI = indirectly standardized concentration index
2) HI = $CI_{latent} – CI_{predicted}$
3) Erreygers CI = $4*\mu*CI_{is}$

A few comparisons from the table are interesting. When looking at the standard Concentration Index (CI), inequality in mammography is at least twice as large in all models for income-related inequality, when compared to cervical screening. However, the same cannot be observed for overall unfair inequality. The Erreygers corrected concentration index, in turn, produces a different pattern. This index takes into account the mean of the observed variable and ensures that mirroring property, transitivity and monotonicity hold, while at the same time ensures consistency and level of independence. When using this index for comparison, the difference between inequality in cervical and mammography screening is much smaller. Mammography still appears to be more inequitable in the basic model, both in terms of income-related as well as overall inequality. Nonetheless, in the comprehensive model, for overall inequality, the measure for cervical surpasses that of mammography screening, reflecting the sensitivity of this index to the mean (larger for cervical than for mammography, in this case). In fact, when observing the Erreygers modified index, in terms of overall unfair inequality, the transition from the basic to the comprehensive model produces an increase of 18.24 percentage points (pp) in the CI for cervical screening, whereas for mammography the increase is only of 5.1 pp.

The comparison between income-related and overall inequality seems straightforward: once more variables are included, the difference between the multivariate and bivariate approaches becomes larger, reaching a maximum of 111.8% for the case of cervical screening (in terms of Erreygers CI). Therefore, the results indicate that, unsurprisingly, overall unfair inequality in the preventive care for women is higher than income-related inequality in the same type of care.

5.4.3 Decomposition of the Overall Inequality Concentration Index

Table 5.6 presents the percentage contribution of each factor to the measure of overall inequality, excluding the residual. This has been calculated using the Erreygers CI as a reference, due to its desireable properties, but the same method could be applied to the other alternative indices reported. For the sake of simplicity, we re-ran the models treating age and categorical covariates (education, region, ethnicity, family type and seatbelt preference) as continuous or ordinal variables as appropriate, rather than large sets of dummies, as this would substantially lengthen the table. Where no natural ranking could be obtained, categorical variables were ordered in terms of the likelihood of receiving care. For example, region was ordered from North (lowest likelihood) to South-East (highest likelihood). Similarly, ethnicity was ordered from Native (lowest probability of receiving care) to white (highest probability). The same logic was applied to the ordering of family-type.

Table 5.6 – Decomposition of the Erreygers Concentration index for overall inequality

(in percentage contribution)

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

	Mammography		**Cervical Screening**	
	Basic	Comprehensive	Basic	Comprehensive
Employment Status	-	0.00%	-	2.34%
Ethnicity	-	0.53%	-	0.27%
Urban Status	-	1.75%	-	0.97%
Family Type	-	6.30%	-	3.76%
Education	-	8.97%	-	3.29%
Region	-	13.31%	-	3.10%
Income	94.37%	16.40%	96.50%	4.48%
Health Insurance	-	44.70%	-	75.84%
Residual	5.63%	7.78%	3.51%	6.23%

As one can see, in the basic model virtually all inequality comes from income. In the comprehensive model, the relative importance of coverage by health insurance is a greater in cervical screening than it is in mammography. This may explain the large increase in the measure of overall inequality in cervical screening moving from the basic to the comprehensive model. As health insurance is the main driver of overall unfair inequality in this service, its inclusion as a covariate produces a large increase in the measure of inequality.

5.4.5 Income-related vs. Overall unfair inequality: gaps and ratios

Another way of looking at inequality is by observing gaps and ratios between quintile groups. While a gap provides information regarding inequality in absolute terms, ratios give relative measures. Table 5.7 presents the gaps and ratios for mammography and Table 5.8 does the same for cervical screening. The tables present results for both models. The gaps and ratios were calculated using the fair determinant adjusted use in each case. For the basic model, the only fair variable was age. Thus, fair determinant is in the case equivalent to need-adjusted predicted probability of use. For the comprehensive model, however, the seatbelt variable was also considered a fair factor, as it proxies behavior towards seeking health care. For illustrative purposes, we have shown the gap, expressed in percentage points, using both the highest quintile group (better off) and the middle quintile group (mean). Ratios were also presented using the two different reference groups.

The tables are consistent with our findings in the concentration indices. As we move from the basic to the comprehensive model, the absolute gap increases for overall inequality and decreases for income-related inequality in the two forms of preventive care analyzed. In general, inequality is larger for mammography screening both in absolute, as well as in relative terms. However, the apparent much smaller relative inequality in cervical screening is derived from its higher utilization. As more women are being screened across all quintile groups, the relative difference between the better and worse off is smaller. The absolute measure is still large, according to the basic model, a woman in the most deprived group is16.6 pp less likely to receive care. Such number goes up to 20.3pp in the comprehensive model, in terms of overall inequality.

Table 5.7 – Absolute and relative income-related and overall inequality in mammography

Mammography	GAP (highest quintile group)	GAP (middle quintile group)	Ratio (highest quintile group)	Ratio (middle quintile group)
BASIC MODEL				
Income-related inequality				
Quintiles of equivalised household income				
Lowest quintile	-21.79	-7.65	-38.1%	-17.8%
2	-19.31	-5.17	-33.8%	-12.0%
3	-14.14	-	-24.7%	-
4	-5.61	8.53	-9.8%	19.8%
Highest quintile	-	14.14	-	32.9%
Overall unfair inequality				
Quintiles of health care advantage				
Lowest quintile	-21.80	-7.58	-38.2%	-17.7%
2	-19.38	-5.16	-33.9%	-12.0%
3	-14.22	-	-24.9%	-
4	-5.59	8.63	-9.8%	20.1%
Highest quintile	-	14.22	-	33.1%
COMPREHENSIVE MODEL				
Income-related inequality				
Quintiles of equivalised household income				
Lowest quintile	-9.90	-2.68	-21.9%	-7.0%
2	-9.12	-1.90	-20.2%	-5.0%
3	-7.22	-	-16.0%	-
4	-2.00	5.22	-4.4%	13.7%
Highest quintile	-	7.22	-	19.0%
Overall unfair inequality				
Quintiles of health care advantage				
Lowest quintile	-33.25	-10.27	-58.5%	-30.3%
2	-28.53	-5.55	-50.2%	-16.4%
3	-22.98	-	-40.4%	-
4	-16.84	6.13	-29.6%	18.1%
Highest quintile	-	22.98	-	67.8%

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

Table 5.8 – Absolute and relative income-related and overall inequality in cervical screening

Cervical Screening	GAP (highest quintile group)	GAP (middle quintile group)	Ratio (highest quintile group)	Ratio (middle quintile group)
BASIC MODEL				
Income-related inequality				
Quintiles of equivalised household income				
Lowest quintile	-16.60	-6.88	-19.6%	-9.2%
2	-12.68	-2.96	-15.0%	-4.0%
3	-9.71	-	-11.5%	-
4	-2.76	6.96	-3.3%	9.3%
Highest quintile	-	9.71	-	13.0%
Overall unfair inequality				
Quintiles of health care advantage				
Lowest quintile	-16.32	-6.71	-19.4%	-9.0%
2	-12.92	-3.31	-15.3%	-4.4%
3	-9.61	-	-11.4%	-
4	-2.46	7.16	-2.9%	9.6%
Highest quintile	-	9.61	-	12.9%
COMPREHENSIVE MODEL				
Income-related inequality				
Quintiles of equivalised household income				
Lowest quintile	-3.99	-1.46	-7.0%	-2.7%
2	-3.58	-1.04	-6.3%	-1.9%
3	-2.54	-	-4.4%	-
4	-0.58	1.96	-1.0%	3.6%
Highest quintile	-	2.54	-	4.6%
Overall unfair inequality				
Quintiles of health care advantage				
Lowest quintile	-20.30	-11.20	-23.3%	-14.3%
2	-18.01	-8.90	-20.7%	-11.4%
3	-9.11	-	-10.5%	-
4	-5.09	4.02	-5.8%	5.2%
Highest quintile	-	9.11	-	11.7%

Source: National Household Sample Survey (PNAD), Health Supplement, 2008

5.5 Discussion and concluding remarks

5.5.1 Main findings

We have shown that both income-related and overall unfair inequality in preventive care for women in Brazil exists. From the initial descriptive statistics of proportion of women using the service by income quintile (Table 5.2), we could already note that the case of mammography was worse. Whereas the gap existing between the richest and poorest quintiles was circa 20 percentage points for cervical screening, this same gap is 50% larger for mammography. Two elements may contribute to this fact. Firstly, the National Cancer Screening Program is Brazil stipulates that women aged 25 to 49 should be screened every three years, whereas bi-yearly mammography screening is directed at women aged 40 or more, and more consistently targets women aged between 50 and 69 (INCA, 2013, CONASS, 2011, Parada et al., 2008). Targeting a smaller and older group of women may indeed result in larger inequality. Secondly, while cervical screening only depends on a health care professional and a swab to take place, mammograms are capital-intensive diagnostic exams, as they depend on mammogram scanners and appropriate environment for such. Thus, there is reason to believe that some other factors are in play in the case of mammography screening.

Also consistent with the National Cancer Screening Program is the increased likelihood of women in the target population to be screened. As tables 5.3 and 5.4 show, women aged between 40 and 49 are 18.6 percentage points more likely to undergo mammography screening than their younger than 25 counterparts. For women aged 50-59, the probability of screening is increased by 12.1 percentage points. Although the numbers show that young women are the least likely to have a mammography, the higher likelihood lies in the 40 to 49 group. Similarly, the highest marginal effect in terms of age for cervical screening can be found in the group 25 to 39.

The positive marginal effects are indicative of movement in the right direction in terms of policy, but from our study we cannot imply causality. Thus, we cannot say that the increased likelihood of screening for such groups is caused by the program. We can only say that a positive correlation exists. It would also be interesting to observe if this pattern changes in the future, as the policy for mammography has increased periodicity for women aged 50 – 69.

Still in terms of mammography screening, Table 5.3 shows that women in the South East region are the better off. A tentative explanation of this fact relies on the fact that most of the mammography equipment are concentrated in such region, thus it is easier to get a mammography if living in the South East. This could be a indicative of supply-side factors resulting in inequality. Another interesting positive correlation, which can be observed in mammography screening, relates to employment and the capital-intensive procedure. While for physician visits, as seen in the previous chapter, and for cervical, unemployed women are more likely to receive care, the opposite happens in the case of mammography. Whether that is attributable to the capital-intensive nature of such or there are other factors that may explain this correlation, one cannot grasp from the present study.

Particular contributors to inequity vary between the two outcome variables, although coverage by health insurance is the most important driver in both cases according to the comprehensive model. When insurance is taken into consideration, more than ¾ of the inequality can be explained by this factor in cervical screening. In this case, income accounts for less than 5% of inequity. In mammography screening, health insurance coverage is never as significant, although it still accounts for more than 44% of the inequality. In this form of preventive care, income accounts for circa 15%, region for more than 10%.

5.5.2 Policy implications

Women's health has been studied for the past 30 years not only for its centrality in reproduction, but also because of the increase in women’s participation in the labour market, her importance in the upbringing of children and maintenance of households (Marques et al., 2011b, Valdés and Gomáriz, 1995). These are some of the background reasons for policy concern that focus on preventive care for women. The current study has several policy implications. First, as already mentioned, the larger inequality for mammography may be provide an indication of supply-side constraints in terms of the availability of the machinery and its capital-intensive nature. A lower mean use is important here. When observing the Erreygers CI, the difference between the measures of overall inequality is not as large (0.345 and 0.259 respectively). The contributors to inequality, on turn, also indicate that policy approaches should be different for each form of care. For cervical screening, the main drivers are related to socioeconomic status, and therefore policies enabling access of the poorest segments of the population would possibly decrease inequality more effectively than alternative action. For mammography, less than 40% of the inequality is income-related, suggesting that some action directed at the least educated and residents of areas were care is less frequent, especially the North and North-East, may be more or at least as beneficial as actions towards securing universality of access. Here again, it appears that certain areas experience lack of supply of care. If this were indeed the case, inequality could be decrease by correctly equipping such regions.

5.5.3 Comparison with previous literature

The current chapter has demonstrated that overall unfair and income-related inequality in preventive care for women exists. In general, the calculated models and indices have shown that overall inequality is higher than the income-related inequality in mammography and cervical screening, although the former is consistently more inequitable than the later, both using the bivariate approach as well as the health care advantage approach.

The findings that inequality in preventive care is larger than in curative care, as observed in the previous chapter, is consistent with the literature (Frohlich and Potvin, 2008, Lorant et al., 2002). Comparability between studies is somewhat difficult, as not all report in terms of gaps and ratios or concentration indices (Palencia et al., 2010, Couture et al., 2008). For two that do, however, the magnitude of the existing income-related inequality is smaller than that observed in this study (Moser et al., 2009, Lorant et al., 2002).

5.5.4 Strengths, limitations and future research

In this paper, we have applied the health care advantage approach developed in the previous chapter to measure overall unfair inequality in preventive care for women. We have used the approach to produce several measures of inequality, including three forms of concentration indices as well as gaps and ratios. This consists in one of the strengths of this approach. The health care rank provides an ordering of people in terms of their advantage given the factors placed in the unfair vector of healthcare determinants. The new ordering permits the application of tested methods for measuring inequality. We have only reported a few. Nonetheless, no comparison to previous studies was possible in terms of overall unfair inequality in preventive care for women, as to our knowledge no other study has the method here presented into a different setting.

The selection of preventive care outcome variables is also a strength of the chapter. Unlike other forms of care, preventive care has a much more limited need component to it. One can argue that all individuals are at risk of disease, there is uncertainty around it and unless we have a way of accounting for genetic endowment, only age influences the likelihood of developing breast and cervical cancer. This levels up all women in terms of health needs, which is an interesting feature when studying inequality.

As usual, the study also has its limitations. Potential reporting bias exists, as the measures of health care are self-reported. We also assume that women of any ethnic background are at the same risk of developing breast or cervical cancer, thus, there is equivalent level of need for preventive care, although there is some evidence in the North-American population that black women are more prone to developing these diseases (Mandelblatt et al., 1991, Li et al., 2003). The assumed equality between ethnicities in our case derives from the lack of evidence that points towards different levels of need for health care for the distinct groups. Finally, perhaps the most important limitation of the current study is the lack of causal implications. We have been able to present the magnitude of inequality and unfair factors contributing to it. We have not, however, been able to point to factors that cause inequality, which would be particularly interesting to policy makers.

Some of the points raised in the discussion remain questions to be answered in future research. Especially the existence of supply-side constraints is intriguing and deserves better investigation. Measurement of overall inequality in other capital-intensive procedures may also be an avenue of research to be explored in the future.

Chapter 6: Evolution of unfair inequality in the Brazilian National Health Care system: an application of the Health Care Advantage Rank (HCA Rank)

Abstract

This paper applies the Health Care Advantage approach to measure overall unfair inequity in healthcare in Brazil and looks at how such inequality has varied between 1998 and 2013. By splitting covariates into two vectors, fair versus unfair sources of inequality, the HCA approach allows for different normative views regarding which factors constitute socially objectionable sources of inequality. The full list of potentially "unfair" sources of inequality includes equivalised income, education, region, urban/rural status, family type, ethnicity, employment status and private health insurance coverage. I have been able to decompose the relative contribution of each factor to overall unfair inequality on the assumption that all of these variables count as are "unfair". This decomposition then gives the reader an indication of how far the unfair inequality measure would be reduced if a particular factor were removed from the list of "unfair" sources of inequality. I have focused on three outcome variables, namely physician visits, mammography screening and cervical screening. The variables were chosen given that National Policies were put in place during the period of analysis, so variation regarding the use of service existed. The data came from Health Supplement of the National Household Sample Survey for the years 1998, 2003 and 2008 and from the first National Health Survey for 2013. Sample sizes have varied, but were always in excess of 300 thousand individuals and representative of Brazil at national and regional levels. I reported the results using the standard concentration index (CI), the horizontal inequity index (HI) and the Erreygers modified concentration index (Erreygers CI), allowing for a few different normative positions. Results show that overall unfair inequality in physician visits decreased over time by more than 40%, when using the CI and HI approaches. For cervical screening the reduction reached 17%, although for mammography screening the decrease was small. The results also show that the coverage of health insurance has become the most important source of inequality as time went by and income, having children in the household and living in urban areas are becoming less important, with the exception of cervical screening, for which income seems to have doubled its importance between 2003 and 2013.

6.1 Introduction

Previous studies (Macinko and Lima-Costa, 2012, Almeida et al., 2013) found a decrease in income-related inequality in physician visits in Brazil from 1998 to 2008. The current chapter updates and substantially extends this analysis by looking at trends in overall inequality in healthcare use from 1998 to 2013. It adds value to the previous analysis in four ways. First, by looking at overall unfair inequality rather than just income-related inequality. Second, by decomposing inequality trends by different sources of unfair inequality including income, ethnicity, educational achievement, region, employment status, urban/rural status, family type and health insurance coverage. Third by comparing trends in physician visits with trends in two different types of cancer screening, one of which requires access to high-tech machinery (mammography screening) and one of which does not (cervical screening). National programmes were introduced for both types of cancer screening during the middle of the period, alongside continued expansion throughout the period in the family health strategy for improving access to primary care ("Programa Saúde da Família"). Fourth, by incorporating more recent health care data for 2013, made available in August 2015, when the results of the first National Health Survey, performed in the second semester of 2013, were made public.

We find that, using the standard concentration index and horizontal inequity index approaches, unfair overall inequality in health care decreased over time, but more for physician visits and cervical screening than for mammography screening – a more capital intensive form of care – where the inequality remains fairly large.

We also find that over time income becomes less important as a contributor to overall unfair inequality, particularly for physician visits. Furthermore, residing in an urban area goes from being the main driver of inequality in mammography and cervical screening to being a minor contributor, suggesting that the national cancer screening policy succeeded in increasing uptake in the countryside. It is also interesting to note that insurance coverage becomes the more relevant driver of inequality in all three forms of care observed, which, given the fact that we are controlling for income, suggests that the presence of health insurance is influencing behaviour in terms of seeking care.

As variation in inequality in health care is an aspect taken into account by policy makers, the national policies relevant to the procedures analysed in this chapter will be briefly explained next.

6.2 Public policy affecting health care services

Since the establishment of the Brazilian National Health System (Sistema Único de Saúde – SUS) in 1988, several policies were put in place as an attempt to increase access of the population to health services and improve health. A few of these policies are important when interpreting the evolution of unfair inequality over time. As we are observing three outcome variables (physician visits in the past 12 months, mammography screening in the past 2 years and cervical screening in the past 3 years), two specific policies are relevant. They are described below, with particular attention to changes that may have occurred during the period of analysis.

6.2.1 Programa Saúde da Família (PSF)

Programa Saúde da Família (PSF) is the national family health strategy put in place in Brazil by the Ministry of Health, in 1994, with the objective of increasing access and improving primary care within the country. The original idea was to bring health care into people's homes by setting up multidisciplinary groups composed of general practitioners, family doctors, nurses, psychologists and health care agents, which was in charge of a group of families. Health Care agents would visit people's homes and provide an initial assessment and direct them towards the correct form of care. Initially, the programme targeted rural populations, although the national policy always aimed at covering both rural and urban areas. In a second moment, areas of socio-economic deprivation were targeted (Brasil, 2012).

Due to the large geography of Brazil, the programme (later strategy) was implemented gradually. In 1998, only 6.55% of the population were covered. In 2003, this had already jumped to 35.69%. In December 2013, 56.37% of all Brazilian inhabitants were covered, though for that same year, the coverage in rural areas reached over 95%.

In terms of dimension, by the end of 2013, PSF had over 36 thousand multidisciplinary groups and more than 300 thousand community agents, and was present in 5,106 municipalities of the 5,505 existing in Brazil (Vasconcellos, 2013, Mendes and Marques, 2014). Its expenditure reached over R$10 billion for that year, which represented about 8% of the public spending in health care (Brasil, 2013b, Brasil, 2013a).

6.2.2 National Policy for Breast and Cervical Cancer Prevention

The relevant national policy for the cases of mammography and cervical screening is the National Policy for Breast and Cervical Cancer Prevention (CONASS, 2011). Unlike PSF, the national policy on cancer prevention is aimed at a particular segment of women. Specifically, prevention of breast cancer targets women aged between 40 and 69 and cervical cancer prevention is aimed at sexually active women aged 25 to 59. This health policy, in spite of its importance to the population, took a long time to become fully effective, as between the legal framework and actual offering of services more than 7 years went by (INCA, 2013). The policy was first made legal in late 1998, after the 10th anniversary of the Brazilian National Health System. However, the first pilot service offered within the policy realm only took place in 2001. Indeed the policy only became national in terms of coverage in 2005. In this year, over 3 million targeted women underwent mammography screening, settling the national status of the policy (Parada et al., 2008, INCA, 2013).

Originally, in order to prevent cervical cancer, the policy determined that sexually active women aged 25 to 59 should be smear screened every three years. Mammography screenings should happen every other year for women aged 50 to 69, and every 3 years for women aged 40 to 49 (Parada et al., 2008). In May 2013, the policy was changed for mammography screening. Women of the eligible age should be clinically evaluated every year, and the medical professional may request the screening at the point of evaluation. In any case, the periodicity of at least 3 years must be kept (INCA, 2013). As 2013 is the last data point available, we have used the variable mammography screening in the past two years, following the policy up until 2013.

Even though the National Policy for Breast and Colon Cancer Prevention has increased access to health care for women considered at greater risk of cancer, active seeking behaviour is still necessary. The policy aims at seeing more than 80% of women in the targeted group, for both prevention of cervical and breast cancer. Actual numbers, however, fluctuate between 60 and 70% for the first form of care, and even lower for the second (INCA, 2013).

6.3 Descriptive Statistics

Brazil is a country of large magnitude both in terms of geography as well as population. With more than 200 million inhabitants, over 8,515 million km^2, of which about 30% is occupied by the Amazon rainforest, there are difficulties from a State perspective for providing healthcare, once some areas are more inaccessible. Nonetheless, in the 15-year time frame of analysis, several general characteristics of the population have changed. To start with, between 1998 and 2013 the population has grown in more than 34 million people. In terms of national income, GDP per capita in PPP terms has nearly double in this time. Also income inequality has decreased, which can be observed in a reduction of the Gini coefficient – from 0.600 in 1998 to 0.527 in 2013. Studies have shown that the decrease in income inequality was a result of increases in income of the poorer segments of the population, which benefited from the government’s policy to consistently increase the minimum wage in real terms (Holzhacker and Balbachevsky, 2007, Morais and Saad-Filho, 2011, Bresser-Pereira, 2013)

In terms of medical care, the population gained coverage of PSF, a slight increase in health insurance coverage was observed, and the number of people visiting the doctor yearly has increased by nearly 20 percentage points (p.p.). A large increase (more than 15 p.p.) in mammography screening between 2003 and 2013 is also observable. The increase in cervical screening, in turn, is much more modest, although still existing. Table 6.1 summarizes the most important general and health related population characteristics by survey year.

Table 6.1 – Population Characteristics by Survey Year (1998, 2003, 2008 and 2013)

	1998	2003	2008	2013
Population (million)*	170.5	183.6	194.7	204.2
GDP per capita (PPP US$/2002)**	8,534	9,661	13,152	15,726
Gini**	0.600	0.583	0.546	0.527
Age (mean)	28.18	29.67	33.16	33.77
Female(%)	51.02%	51.07%	50.75%	52.45%
Urban Residence	81.4%	85.16%	84.2%	87.9%
Unemployment (%)**	9.7.%	10.5%	7.8%	7.1%
Physicians (per 1,000 people)*	1,295	1,503	1,764	1,891
Health expenditure per capita (PPP US$/2011)*	559	657	1,082	1,453
Health expenditure (% of GDP)*	6.7%	7.0%	8.4%	9.6%
Public Health expenditure (% of total)*	42.6%	44.3%	43.8%	48.2%
Coverage by Family Health Strategy (PFS)***	6.6%	35.7%	49.5%	56.4%
Private Health Insurance	24.6%	23.3%	24.5%	26.9%
Reported poor or very poor health	3.66%	3.36%	3.77%	3.08%
Reported good or excellent health	78.7%	78.0%	77.0%	78.9%
Visited the doctor in the past 12 months	55.9%	62.7%	67.3%	72.9%
Had a mammography in the past 2 years	na	40.6%	41.0%	56.3%
Privately insured women who had mammography in the past 2 years	na	54.3%	65.7%	79.8%
Had cervical screening in the past 3 years	na	69.6%	74.3%	76.5%
Privately insured women who had cervical screening in the past 3 years	na	75.4%	85.7%	89.2%

Note: For data collected from surveys, all results take into account complex survey design and survey weights.
Data Source: * World Bank Databese (http://databank.worldbank.org)
** Instituto Brasileiro de Geografia e Estatistica (IBGE)
*** Ministry of Health. Sala de Apoio a Gestao Estrategica (http://189.28.128.178/sage/)
National Survey of Household Samples (PNAD) 1998, 2003 and 2008 and National Health Survey (PNS) 2013.

6.4 Methods

As I have mentioned in previous chapters, the measure of overall unfair inequity in healthcare depends on a choice of fair and unfair contributors to inequality. In general, healthcare can be seen as a function of fair sources of inequality, as well as unfair sources. For the modelling in this chapter, I was restricted by the data available in each wave of the surveys, and thus, my vector of fair sources of inequality include sex, age and self-assessed health for physician visits, and age only for mammography and cervical screening, as these two variables are women-only and self-assessed health was found to be statistically insignificant.

Regarding the vector of unfair sources of inequality, I have included equivalised household income (in natural logscale), ethnicity, educational achievement, region, employment status, urban/rural status, family type and private health insurance coverage, as these are available in all survey waves and could, in my understanding, potentially produce unfair inequality. Unfortunately, the variable seatbelt use was not available for all the waves analysed. Thus, I could not model preference for medical care, proxied by seatbelt use, as I have done in previous chapters. The standardising regressions have followed equation [1], which specifies the individual measure of direct unfairness:

$$hc_{du} = hc_{predicted}\ (N_{ref},\ ,\ SES_i,\ Z_i) \qquad [1]$$

Where N stands for need-factors, considered fair sources of inequality, SES stands for socio-economic status, and Z stands for other socio-demographic variables, also considered unfair in this analysis.

Based on the fair-predicted healthcare use, I could establish the Health Care Advantage Rank (HCA) for each outcome and year. Given that the main objective of this chapter is looking at variation over time in overall inequality and its unfair component, the directly standardised standard and Erreygers modified Concentration Indices were calculated, along with the Horizontal Inequity Index for each of the outcome variables at each point in time. In short, the main methodological contribution presented in Chapter 4 – the Health Care Advantage Rank – was applied here in a repeated cross-sectional context, which allows for the observation of trends of the above mentioned indices as well as their decomposition variations, if existing.

6.5 Changes in Overall Unfair inequality

I now turn our attention to how unfair overall inequality has varied between 1998 and 2013 for physician visits and 2003 and 2013 for mammography and cervical screening. As one can see, in all three cases, inequality has decreased overtime, at least when using the standard concentration index. Table 6.2 shows the measures of inequality based on the Health Care Advantage Rank, using the traditional Concentration Index and Horizontal Inequity Index measures, as often reported by the ECuity Project, and finally the Erreygers correction to the Concentration Index, due to its interesting properties of mirror, monotonicity and level of independence, although it no longer can be considered a measure of relative inequality (Erreygers, 2009, Wagstaff, 2009). Each of these measures has its own set of normative implications, and one may feel more inclined towards one or another. I appreciate the interesting debate existing regarding the most appropriate index to use when dealing with binary variables and healthcare, as is the case here (Wagstaff, 2011a, Wagstaff, 2011b, Erreygers and Van Ourti, 2011b, Erreygers and Van Ourti, 2011a). However, I have made the choice of reporting in all three formats, not only for the sake of completeness, but also taking into consideration the attributes and advantages of each, as well as the normative judgments implied.

Table 6.2 – Overall health care inequality indices by year

	1998	2003	2008	2013	Change from baseline
		Physician Visits			
CI	0.1251	0.1003	0.0700	0.0690	44.9%
HI	0.1163	0.0929	0.0649	0.0588	49.5%
Erreygers CI	0.2796	0.2513	0.1883	0.2010	28.1%
		Mammography			
CI		0.2161	0.2122	0.2099	2.9%
HI		0.2779	0.2752	0.2586	6.9%
Erreygers CI		0.3507	0.3477	0.4726	-34.8%
		Cervical Screening			
CI		0.1465	0.1353	0.1215	17.1%
HI		0.1816	0.1529	0.1513	16.7%
Erreygers CI		0.4078	0.4024	0.3717	8.9%

Data Source: PNAD 1998, 2003 and 2008 PNS 2013.
Notes: 1) The CI is the standard CI of fair-determinant-standardized utilization;
2) HI = $CI_{observed} - CI_{predicted}$.
3) Erreygers CI = 4*μ*CI
4) The mammography and cervical screening questions were not included in the survey in 1998.
5) Baseline for physician visits in 1998 and for Mammography and Cervical Screening is 2003.

From Table 6.2, one clearly sees that the reduction in overall inequality is greater for physician visits, where a reduction of over 40% is observed both in terms of the standard CI and the HI. According to the Erreygers CI inequality in physician visits increased from 2008 to 2013 though not according to the other two indices; this discrepancy is because the Erreygers correction allows for change in the mean to be reflected in the index. As said before, this implies a normative judgment, in which one is concerned not only with the extremes in a population, but also the distribution in the middle groups, and is a result of the quasi-absoluteness property of the measure (Erreygers and Van Ourti, 2011a, Erreygers and Van Ourti, 2011b).

It is worth recalling that each of the calculated measures of inequality has a different underlying normative assumption. For instance, whilst the Erreygers index reflects the perception that more individuals on the upper part of the distribution are receiving care, for example, inequality is larger, the standard concentration index places more weight on transfers affecting the middle groups of the distribution. Different researchers may be more inclined to one measure of inequality or the other, depending on the question addressed and their own normative judgement.

From the table, one also sees that for mammography the inequality measured by Erreygers CI increases with time, clearly reflecting a larger mean use of the service, once the CI has only decreased by 2.9%. Finally, inequality in cancer screening is in both instances larger than that in physician visits across the population. This may be due to a difficulty of the policy in reaching the targeted population for both cases. Finally for mammography screening, a dependence on capital-intensive equipment is also relevant, which may contribute to a higher degree of inequality and a flatter decrease rate. Tables 6.3[12] (a), (b) and (c) provide the results of the standardizing logistic regressions used to produce the indexes in terms of marginal effects[13].

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[12] Sample sizes refer to eligible patients, which for physician visits includes men and women of any age group and for cervical screening and mammography includes only women aged 15+.

[13] Tables presenting the odds ratios and respective standard errors (SE) of standardizing regression can be found in Appendix C.

Tables 6.3 (a) – Marginal Effects – Physician Visits

	1998	2003	2008	2013
	mg effect	**mg effect**	**mg effect**	**mg effect**
ln(Income)	0.014	0.013	0.017	0.011
<u>NEED FACTORS</u>				
Male (base)				
Female	0.063	0.072	0.186	0.125
Age group (base: younger than 15 years of age)				
15 - 29	0.093	0.119	0.095	0.012
30 - 44	0.233	0.196	0.121	0.116
45 - 60	0.179	0.184*	0.147	0.121
60 +	0.016	0.020	0.029	0.039
Self-Assessed Health (base: Very Good Health)				
Good	0.091	0.076	0.071	0.041
Regular	0.324	0.276	0.236	0.150
Bad	0.337	0.369	0.342	0.215
Very Bad	0.391	0.330	0.331	0.239
<u>NON - NEED FACTORS</u>				
Educational Achievement (base: no education)				
Primary	-0.056	-0.108	-0.090	-0.033
Secondary	-0.128	-0.106	-0.035	-0.018
Higher	-0.054	-0.119	-0.030	-0.002
Undetermined	-0.067	0.015	0.013	0.004
Region (base: North)				
North East	0.031	0.006	0.022	0.019
South	0.049	0.017	0.023	0.055
Centre West	0.053	0.009	0.025	0.062
South East	0.074	0.059	0.056	0.072
Urban (base)				
Rural	-0.088	-0.079	-0.038	-0.011
Ethinicty (base: white)				
Asian	-0.320	-0.160	-0.081	-0.005
Native	-0.190	-0.204	-0.026	-0.028
Black	-0.156	-0.223	-0.009	-0.022
Mixed	-0.152	-0.205	-0.010	0.028
Emplyment Status (base: occupied)				
Unoccupied	0.047	0.015	0.025	0.015
Family Type (base: no children)				
children under 14	-0.064	-0.079	-0.039	-0.007
children 14+	0.104	0.128	0.012	0.074
Health Insurance (base: No)				
Yes	0.203	0.212	0.136	0.171
Adjusted R-squared	0.110	0.099	0.119	0.127
Number of observations	33533	38351	39871	40186

Data Source: PNAD 1998, 2003 and 2008 PNS 2013.
Note: All values significant at 1%. * Significant at 5%.

Tables 6.3 (b) – Marginal Effects– Mammography Screening

	2003	2008	2013
	mg effect	**mg effect**	**mg effect**
ln(Income)	0.062	0.044	0.086
<u>**NEED FACTORS**</u>			
Age group (base: younger than 25 years of age)			
25 - 39	0.064	0.065	0.079
40 - 49	0.216	0.179	0.099
50 - 59	0.286	0.203	0.096
60 +	0.043*	0.017	0.014
<u>**NON - NEED FACTORS**</u>			
Educational Achievement (base: no education)			
Primary	0.089	0.071	0.074
Secondary	0.131	0.100	0.104
Higher	0.144	0.130	0.148
Undetermined	0.100	0.083	0.042
Region (base: North)			
North East	0.086	0.022	0.012
South	0.095	0.044	0.100
Centre West	0.114	0.055	0.089
South East	0.135	0.106	0.095
Urban (base)			
Rural	-0.116	-0.072	-0.021
Ethnicity (base: white)			
Mixed	-0.157	-0.014	-0.221
Native	-0.155	-0.010	-0.093
Black	-0.068	-0.012	-0.112
Asian	0.006*	0.010	0.111
Employment Status (base: occupied)			
Unoccupied	0.007	-0.037	-0.018
Family Type (base: no children)			
children under 14	-0.041	-0.027	-0.032
children 14+	0.117	0.028	0.081
Health Insurance (base: No)			
Yes	0.049	0.157	0.188
Adjusted R-squared	0.1264	0.129	0.109
Number of observations	10703	14214	12669

Data Source: PNAD 1998, 2003 and 2008 PNS 2013.
Note: All values significant at 1%.
* Significant at 5%.

Tables 6.3 (c) – Marginal Effects– Cervical Screening

	2003	2008	2013
	mg effect	**mg effect**	**mg effect**
ln(Income)	0.020	0.038	0.012
NEED FACTORS			
Age group (base: younger than 25 years of age)			
25 - 39	0.108	0.169	0.167
40 - 49	0.093	0.164	0.174
50 - 59	0.012	0.066	0.076
60 +	0.029	0.075	-0.063
NON - NEED FACTORS			
Educational Achievement (base: no education)			
Primary	0.042	0.058	0.044
Secondary	0.049	0.101	0.045
Higher	0.110	0.154	0.089
Undetermined	0.025	0.058	0.034
Region (base: North)			
North East	0.027	0.004	0.001
South	0.082	0.015	0.053
Centre West	0.099	0.002	0.076
South East	0.079	0.022	0.080
Urban (base)			
Rural	-0.179	-0.021	0.036
Ethinicty (base: white)			
Mixed	-0.820	-0.073	-0.127
Black	-0.292	-0.050	-0.168
Native	-0.091	-0.086	-0.144
Asian	-0.051	-0.068	-0.231
Emplyment Status (base: occupied)			
Unoccupied	0.034	0.044	0.033
Family Type (base: no children)			
children under 14	-0.050	-0.027	-0.008
children 14+	0.090	0.074	0.104
Health Insurance (base: No)			
Yes	0.079	0.162	0.182
Adjusted R-squared	0.117	0.075	0.080
Number of observations	10709	10056	9301

Data Source: PNAD 2003 and 2008 PNS 2013.
Note: All values significant at 1%.

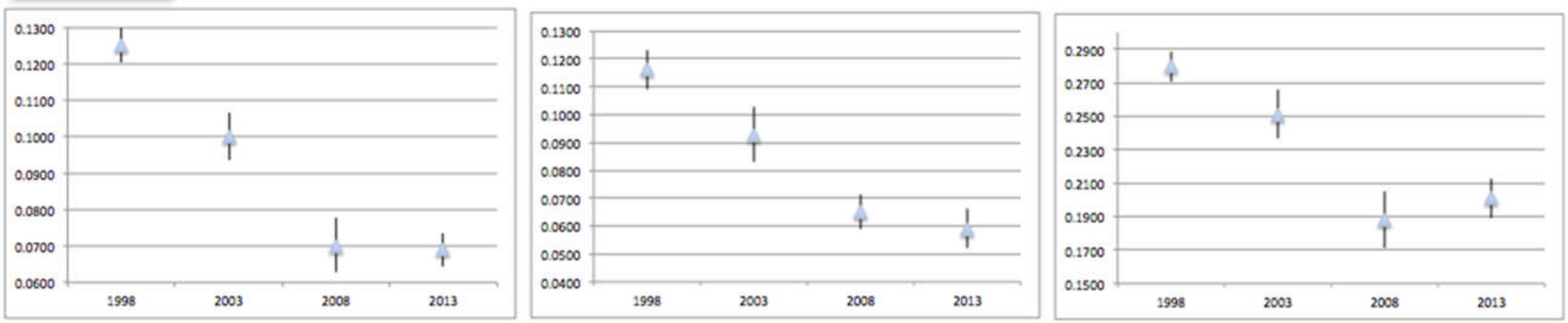
From Tables 6.3, one sees that for physician visits only, uneducated people more likely to receive care, which may be interpreted as them being better off in terms of health care compared to their educated peers at any level, if one considers that more care is better than less care. However, as expected, white individuals living in cities are always better off. Being unemployed appears to have a positive effect on the use of healthcare, as does having health insurance. The type of family is interesting, once families with young kids use the services less than their childless counterpart, but just the opposite happens to family with older children. Finally, even though a clear and opposite pattern can be seen within Asians, namely that use of care has decreased in physician visits and increased in cervical screening in the period analyzed, it is difficult to reasonably explain this, particularly if one considers that they are under 0.5% of the population, so in the sample taken, they would only include between one and two hundred individuals (131, 125, 151 and 175 for each year respectively). Whilst one could hypothesize that the difference in patterns relates to health care seeking behaviour among Asians, any conclusions regarding this subgroup of population should be parsimonious, given the small sample size.

Figures 6.1 (a), (b) and (c) present the trends of the calculated indices and their correspondent 95% confidence interval.

Figure 6.1 – Inequality changes over time

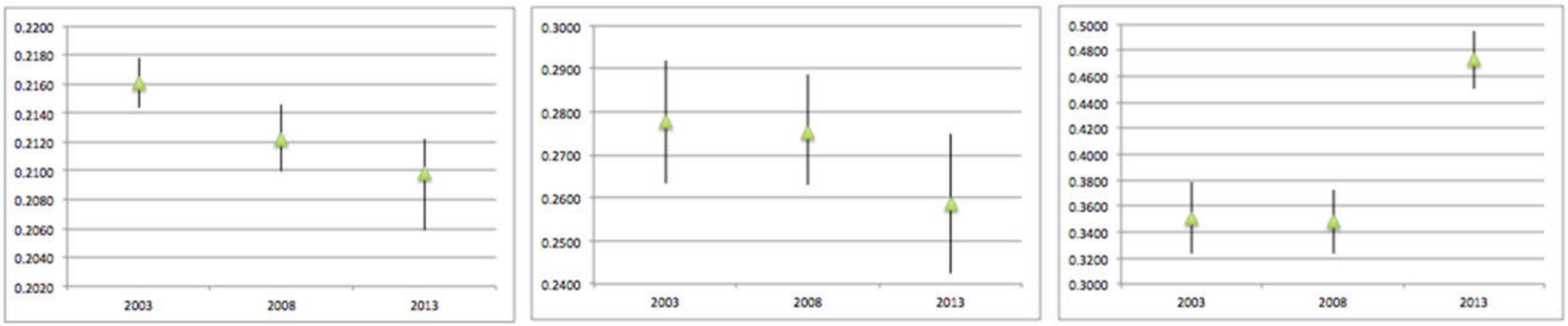
(a) Physician Visits

CI HI Erreygers CI



(b) Mammography Screening

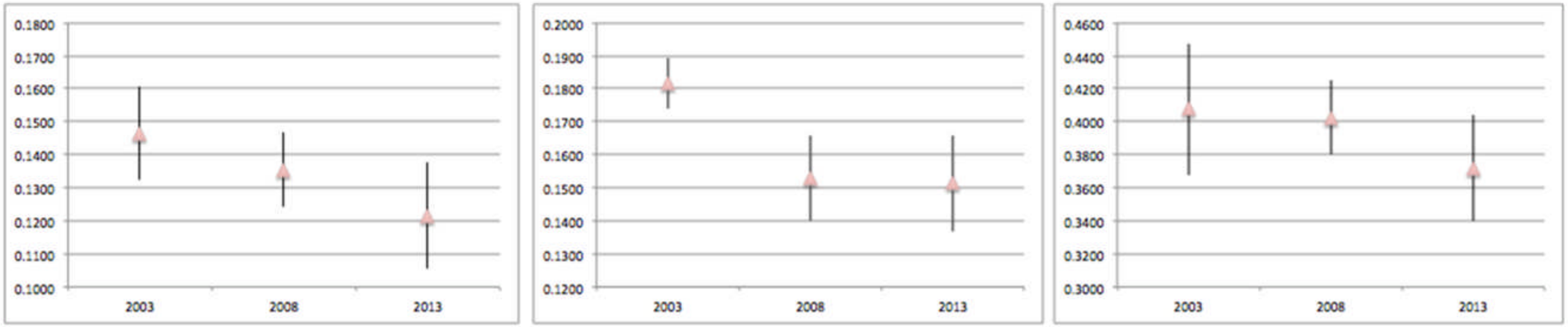
CI HI Erreygers CI



Data Source: PNAD 2003 and 2008 PNS 2013.

(c) Cervical Screening

CI HI Erreygers CI



Data Source: PNAD 2003 and 2008 PNS 2013.

As we can see from Figures 6.1, the most significant change in overall unfair inequality was achieved in physician, particularly between the years 2003 and 2008, there index decreased by about 30%, from 0.1003 to 0.0700. However, reductions were also observed in cervical screening and mammography screening, even though the later the magnitude is fairly small, which can be perceived by the scale of reduction. Furthermore, when focusing on the standard concentration index (CI), it seems that in both the cases of mammography and cervical screening the trend appears to be linear. More interestingly, when looking at the different indices, in the Erreygers CI for physician, there is an inflexion in 2008, and inequality grows in 2013. The case of mammography is even more diametrical. Whereas inequality is decreasing according to the CI, it is increasing in terms of Erreygers. The differences are not only mathematical, but imply a different concern in terms of inequality.

In a country like Brazil, where resources are not very well distributed, both absolute and relative measures of inequality are important. If we consider that the care received by those who are in a better off position, than our main preoccupation would fall upon the most deprived groups. Table 6.4 shows the absolute gap between the better and worse off groups for several variables. For the outcome variables, I have compared the use of the service by the best-off quintile group in terms of Health Care Advantage and unlucky worst-off quintile. For all unfair sources of inequality, I have compared the fair-determinant standardized use of physician visits, although the better off and worse off categories have varied. For income, I used the richest versus the poorest quintile, for education, higher education consisted the better off and no education, the worse off. Likewise, the South-East was compared to the North, white individuals to mixed race, Urban to Rural inhabitants, employed to unemployed, families with children over the age of 14 to families with children under 14 and people with health insurance to people without.

Table 6.4 – Absolute gap between most and least deprived groups by category

in percentage points

	1998	2003	2008	2013	Better off/Worse off group
Physician Visits	8.2	7.8	7.8	5.6	
Mammography		18.2	13.0	11.5	
Cervical Screening		12.7	11.7	7.0	
Income	14.0	15.1	7.7	5.5	
Education	7.0	8.0	7.2	5.7	Higher Education / No Education
Region	3.3	4.1	6.5	5.6	South-East / North
Ethnicity	3.4	3.7	4.7	4.2	White / Mixed
Urban/Rural	4.2	4.5	4.4	4.2	
Employment Status	0.1	0.3	0.4	0.2	
Family Type	5.2	5.4	5.0	3.2	Children over 14 / Children under 14
Health Insurance	6.7	7.6	13.0	12.7	

Data Source: PNAD 1998, 2003 and 2008 PNS 2013.
Notes: 1) For Physician Visits, Mammography and Cervical Screening, the groups compared were the first and fifth quintiles of people ranked according the Health Care Advantage Rank;
2) For income, the comparison was between the richest and poorest quintiles.
3) Where several groups exist, I chose to compare the most deprived with the better off. Each is stated in the Table.
4) For unfair social determinants, comparison is based on fair-determinant standardized use of physician visits.

From the table, it is clear that even though the difference in percentage points in decreasing for all forms of care analyzed, it is still large, particularly for mammography. It is also interesting to note that the difference in use of care by income has decreased roughly in the same proportion of increase when comparing groups with or without health insurance. Finally, for some sources of unfair inequality the difference between the most deprived and the better off has remained stable in absolute terms, that is the case of ethnicity, urban/rural status and employment status.

Table 6.5 – Relative gap between most and least deprived groups by category

	1998	2003	2008	2013	Better off/Worse off group
Physician Visits	15.4%	12.9%	12.7%	8.1%	
Mammography		90.5%	90.2%	79.6%	
Cervical Screening		19.1%	18.0%	17.3%	
Income	54.9%	44.4%	17.0%	10.8%	Richest Quintile / Poorest quintile
Education	22.5%	20.7%	14.4%	10.7%	Higher Education / No Education
Region	11.5%	11.0%	15.0%	12.0%	South-East / North
Ethnicity	11.7%	9.7%	9.5%	8.0%	White / Mixed
Urban/Rural	15.1%	12.5%	9.2%	7.9%	
Employment Status	0.3%	0.7%	0.8%	0.3%	
Family Type	20.0%	14.6%	9.8%	5.8%	Children over 14 / Children under 14
Health Insurance	22.8%	20.0%	23.4%	27.5%	

Data Source: PNAD 1998, 2003 and 2008 PNS 2013.

On turn, Table 6.5 shows the relative difference between each of those groups. As the mean use of healthcare has increased overall, the difference between the better and worse off may not be so large, given the mean use of the latter group. This is partly what can be apprehended from the table. Indeed for physician visits, mammography screening, income, education, urban/rural status and family type, the difference has decreased in relative terms. It has remained fairly stable for cervical screening and region and increased for health insurance.

6.6 Changes in decomposition

Another feature we are interested in is how much each factor of unfair inequality has contributed to the inequity measure. This is presented in Table 6.6, which decomposes the Concentration Index build based on the Health Care Advantage Rank for each outcome and year. Given that I was interested in looking at percentage contribution, they all add up to 100%, even though as we know, inequality has decreased for the outcome measures in this time.

A few stylized facts can be drawn from the table. First, for physician visits: i) urban status, which accounted for more than 10% of the overall unfair inequality, became less important and even a very small contributor in the last wave; ii) the contribution of income has decreased in a fairly linear fashion; iii) employment status, although never big, became smaller, and the opposite was observed with region; iv) the type of family of the individual is also contributing less and less to inequality and v) health insurance has increased its contribution to inequality and can be considered the main driver of such through the period of analysis.

In the case of mammography: i) health insurance has become the main driver of inequality, although it was not the most important factor at the beginning of the series; ii) income, family type and urban status, which in 2003 represented about a fifth of the inequality each, lost most of its relevance, and in the case of family type, the contribution in 2013 falls below 2%. Finally, regarding cervical screening, the three most noticeable facts are: i) urban status account for more than 50% of the inequality in 2003 and only less than 1.5% in 2013; ii) the importance of health insurance has leaped between 2003 and 2008, which could be an indication that the National Policy on Breast and Cervical Cancer has also impacted the private sector, maybe by making people more aware of the importance of getting screened. Actually, even though the percentage of people screened decreased between 2003 and 2008 in total, it has remained stable for women with health insurance, with just under 70% being screened that year; iii) opposite to the observed in the other two outcomes, the contribution of income has nearly doubled between 2003 and 2013.

Table 6.6 – Percentage contribution to overall inequality in health care

	1998	2003	2008	2013
		Physician Visits		
Residual	8.64%	7.26%	4.73%	5.57%
Ethnicity	0.83%	0.25%	0.28%	0.17%
Employment Status	2.36%	0.96%	0.49%	0.64%
Region	0.63%	0.74%	1.78%	2.58%
Family Type	4.00%	3.92%	2.69%	0.75%
Education	3.73%	3.42%	5.08%	2.12%
Urban Status	10.72%	10.37%	6.78%	0.50%
Income	8.07%	6.57%	5.83%	2.01%
Health Insurance	61.02%	66.52%	72.62%	85.66%
		Mammography		
Residual		5.59%	6.90%	6.82%
Ethnicity		9.45%	2.30%	0.96%
Employment Status		0.71%	0.00%	0.59%
Region		7.99%	11.83%	5.37%
Family Type		17.62%	5.81%	1.32%
Education		2.49%	5.11%	5.60%
Urban Status		14.73%	3.90%	2.99%
Income		21.25%	16.67%	5.87%
Health Insurance		20.15%	47.66%	70.48%
		Cervical Screening		
Residual		8.68%	7.32%	8.09%
Ethnicity		4.57%	0.40%	0.98%
Employment Status		5.97%	6.56%	2.85%
Region		2.51%	2.15%	3.00%
Family Type		6.29%	5.51%	1.83%
Education		1.42%	3.38%	7.45%
Urban Status		51.21%	1.44%	1.49%
Income		3.49%	6.56%	6.88%
Health Insurance		15.85%	66.69%	67.44%

Data Source: PNAD 1998, 2003 and 2008 PNS 2013.

Figures 6.2 to 6.4 display the decomposition of unfair overall inequality for physician visits, mammography and cervical screening. The charts are informative as they display actual contribution to the concentration index, hence give a magnitude of absolute contribution.

Figure 6.2 – Decomposition of overall inequality in Physician Visits

(1998, 2003, 2008 and 2013)

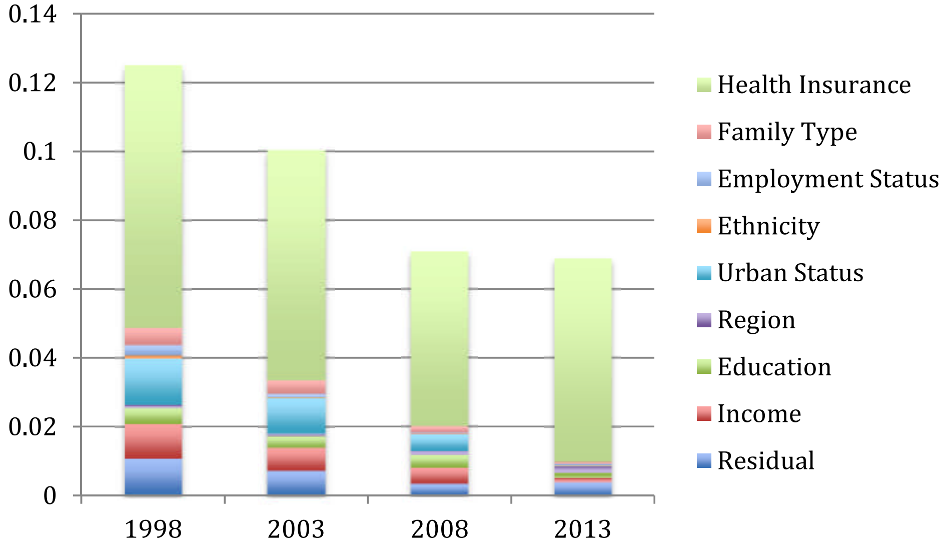


Figure 6.3 – Decomposition of overall inequality in Mammography Screening

(2003, 2008 and 2013)

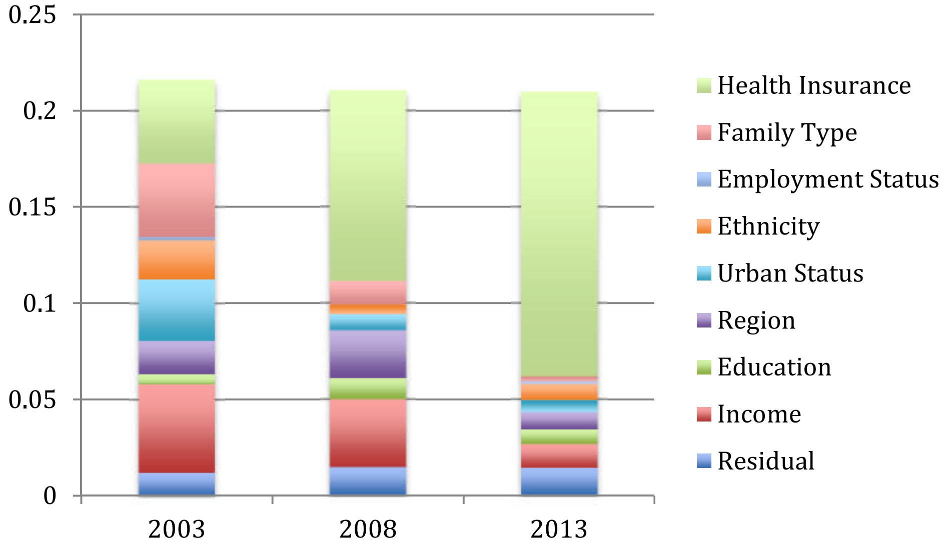
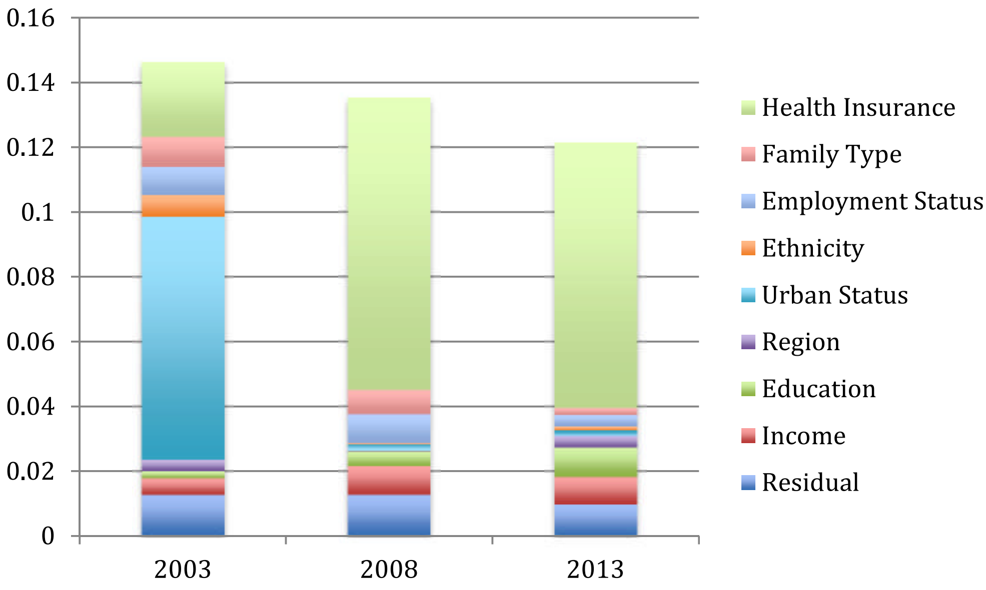


Figure 6.4 – Decomposition of overall inequality in Cervical Screening

(2003, 2008 and 2013)



6.7 Concluding remarks

I have demonstrated throughout this chapter that overall unfair inequality decreased by more than 40% for physician visits between 1998 and 2013 and for cervical screening by more than 15% between 2003 and 2013. For mammography screening the pattern of inequality depends on the index chosen. Inequality regarding the use of this preventive form of care decreases if observing the standard concentration index or the horizontal inequity index, but moves in the opposite direction when using the Erreygers corrected measure.

I have also shown that health insurance is the main driver of inequality currently for all three outcome variables, and that urban status, once a relevant driver of inequality in Brazil, is now only a small contributor. This may well be a result of the deeper penetration of the National Family Health Strategy (Programa Saúde da Família - PSF) and the National Policy on Prevention of Breast and Cervical Cancer, even though the work performed on this study does not infer causality.

Comparing to international literature (van Doorslaer et al., 2000, Bago d'Uva et al., 2009, Devaux and De Looper, 2012, Suárez-Berenguela, 2000, Almeida et al., 2013), the measures of inequality in physician visits observed seem large, but this could be due to a number of things. Firstly, this study focuses on overall unfair inequality, of which income is only a component. As shown in previous chapters, overall inequality is consistently larger than income-related inequality, so larger values found should not be surprising. Secondly, physician visits is a variable that includes general practitioners, family doctors and specialists. In the developed nations, most inequality in GP's visits is pro-poor while specialist visits is pro-rich. As Brazil does not differentiate between the types of doctors in the dataset, it is difficult to compare to international studies. More importantly, even if comparing to previous studies on Brazil, they have focused on income-related inequality and have standardized for chronic conditions, having potentially biased their measure in favor of the rich, once there is a clear slope in the data pointing out that richer people are more prone to disease. Indeed this constitute one of the strengths and a potential limitation of the currently study. By not controlling for measures of morbidity, I am avoiding a potential reporting bias. However, I am perfectly aware that the true estimate should take into consideration measures of health to better estimate the Health Care Advantage Rank.

With regards to Breast and Cervical Cancer screening, previous studies in several countries have found existing inequality, particularly in countries where there is only opportunistic screening and no national policy (Palencia et al., 2010, Couture et al., 2008). In the UK, although inequality in breast and cervical cancer preventive procedures exists, it is small (Moser et al., 2009), unlike the inequality observed in Brazil.

The current study has a number of strengths. To start, sample sizes of individual level data are large and available for at least 3 comparable years, allowing for the analysis of at least a decade. Furthermore, the period of analysis is interesting from a policy perspective, as several policies became effective or expanded. Another advantage of the current study is incorporation of the most recent wave of data, only published in 2015, bringing up-to-date the variation in inequality. Not less important is the fact that I was able to observe multiple unfair determinants of inequality and compare three different types of healthcare utilization.

A number of limitations also exist in this study. Perhaps the most prominent one is the fact that no causation relationship can be inferred from this study, so although the national policies may have affected inequality, the current study does not prove that they have caused the observed reduction nor the direction of causality. Apart from this, by avoiding a potential bias and not using chronic conditions as a control, I may indeed be falling in another, once self-reported health data is often unreliable and biased per se.

Even though the study has a number of shortfalls, it remains relevant for policy makers and it provides unequivocal evidence that health insurance is the main driver of inequality, that inequality in a capital-intensive form of care such as mammography is much larger than inequality in other forms of care and that income is currently only a small part of inequality. This should be carefully considered by policy makers as, in Brazil, having private health insurance is in most cases a consequence of better employment. However, individuals can also directly purchase private health insurance, so it is arguably also a function of income. Future research should not only try to go beyond the currently limitations, but also perhaps develop a budget allocation system that takes into account the current measures of inequality, better establish the relationship between the national policies in place and the decrease in inequality. Another avenue for research is the investigation on how the issue of health insurance being the main driver of inequality should be dealt with. In our models, in spite of the fact that we control for income, having private health insurance is the strongest predictor of receiving care. One could investigate whether this provides an indication of moral hazard.

Chapter 7: Conclusions

7.1 Summary of Principal Findings

Inequalities in healthcare have been extensively studied in high-income countries, but there is relatively less evidence in middle-income countries like Brazil, particularly considering preventive health care. The empirical research in this thesis examined in-detail the present state of affairs regarding healthcare inequalities in physician visits, mammography and cervical screening in Brazil, and how these inequalities have been changing over the past decade. My research has focused on unfair overall inequality as opposed to socio-economic or income-related inequality, following the understanding that inequality is a multifaceted phenomenon towards which many factors can contribute.

I have shown that it is possible to measure overall unfair inequality in a way that is directly comparable to the traditional bivariate approach used to study socioeconomic-related inequality in health care. Based on the individual measures of *direct unfairness* and the *fairness gap*, I have proposed the Health Care Advantage (HCA) rank, which places individuals on a cumulative scale according to their likelihood of receiving appropriate care. For the calculation of measures of inequality, the HCA rank replaces the income or socio-economic rank, allowing for the application of different indices, forms of comparing inequality between groups, including gaps and ratios, and decomposition. I have proposed that the Health Care Advantage approach can be understood as a general framework, in which income or socio-economic related inequality is a special case. This framework is flexible, and allows the researcher to decide which variables to consider as "fair" or "unfair" sources of inequality, and to conduct sensitivity analysis using different ethical assumptions. Under different circumstances, a variable might be placed in the "fair" vector or the "unfair" vector. An example where this decision is controversial is health insurance. One could argue that, after allowing for income, it is fair for people with health insurance to receive more care, as they have freely chosen to pay for this insurance, either explicitly out-of-pocket or implicitly as part of their employment contract. Others might say that being insured is, in a country like Brazil, strongly correlated with better quality employment which in turn may be caused by unobserved aspects of advantageous circumstances beyond individual control, including childhood circumstances such as nutrition, parenting, education and social networks. Regardless of the normative view taken, the approach provides a tool for measuring overall inequality that is considered unfair.

When measuring inequalities in physician visits in Brazil, I found that overall unfair inequality is larger than income-related inequality so long as one considers that education and region are unfair sources of inequality, and larger still if one considers health insurance to be an unfair source of inequality. Overall unfair inequality is at least 21.7% larger than income-related inequality when income, education, region and ethnicity are considered unfair variables. When other variables (urban status, employment status, family type, and health insurance) are included in the unfair vector, overall unfair inequality becomes at least 46.6% larger than income-related inequality.

In terms of contribution to inequality, the most important variables are health insurance, income and education. Other key variables include living in rural areas and family type. I have also argued that previously published studies estimating income-related inequity in physician visits in Brazil may have underestimated the magnitude of inequity. This is because these studies have used self-reported data on chronic conditions to control for need, which is likely substantially to under-estimate need in disadvantaged populations due to under-diagnosis in such populations – as evidenced by the implausible "reverse social gradient" of higher reported prevalence of disease amongst wealthier members of society (Macinko and Lima-Costa, 2012, Almeida et al., 2013).

I have also devoted a chapter of this thesis to measuring and comparing overall unfair and income-related inequality in two forms of preventive cancer screening for women, namely mammography and cervical screening. Inequality in these forms of care may provide an indication of wider health inequalities for women (Moser et al., 2009, Lorant et al., 2002). Being preventive, they also pose an interest with regards to maintaining women fully active, both in the labour market and in the household (Marques et al., 2011a). Finally, for mammography and cervical screening, the measurement of inequality is facilitated given that the level of need women face is dependant only on age.

As was the case with physician visits, for both forms of preventive care studied income-related inequality is smaller than overall unfair inequality. Inequality in mammography is, in general, larger than that observed for cervical screening, which, in turn is larger than measures of inequality in physician visits. For mammography, in the case where variables education, region, ethnicity, employment status, family type, urban status, health insurance coverage and income are deemed unfair sources of inequality, the least health care advantaged quintile group is 58.5% less likely to be screened when in need than the most advantaged quintile group. Although these findings are consistent with the literature, which shows more sizeable inequality in preventive care (Frohlich and Potvin, 2008, Lorant et al., 2002), comparison of magnitudes is difficult. Different studies use different formats to display their results (Palencia et al., 2010, Moser et al., 2009, Couture et al., 2008, Lorant et al., 2002). Nonetheless, one UK-based study found that inequality in mammography and cervical screening, although present, is small (Moser et al., 2009). As I have shown, this was not the case for Brazil.

Finally, I have analysed how overall unfair inequality in all three forms of care has changed between 1998 and 2008 for physician visits, and 2003 and 2013 for mammography and cervical screening. During those time frames, overall inequality in physician visits has reduced in excess of 40%, when observing the standard concentration index, and over 15% for cervical screening, using the same index as reference. For mammography, inequality has decreased by less than 3%, if the standard CI is used as measure of inequality and has actually increased by more than 30% when using the Erreygers corrected CI. This is particularly interesting as mammography is a capital-intensive form of care. Thus the magnitude of inequality being larger and the very small, if any, decrease in inequality in the decade studied suggests that they may be supply factors contributing to inequality, which in our modelling would have been picked up mostly by region and urban status, due to the fact that most mammography equipment are concentrated in the South-East region of the country and in urban areas. The analysis of change in inequality over time was performed considering education, region, ethnicity, employment status, family type, urban status, health insurance coverage and income as unfair sources of inequality. Even though this implies a normative judgement, as we have seen in Chapters 4 and 5 the pattern of findings does not change, only the magnitude of the measures of inequality changes.

Regarding the factors contributing to inequality, the most important factor in all three cases is health insurance. However, the magnitude of its relevance varies between forms of care and changes over time. For physician visits, health insurance started off accounting for more than 60% of the measure of overall unfair inequality and by 2013, it amounted to more than 85% of the measure of unfair inequality. Also for physician visits, between 1998 and 2008, residing in urban areas is more important than income in terms of contribution to overall inequality.

For mammography and cervical screening, health insurance is also an important factor contributing to inequality. By the last wave, in both cases, it accounts for more than two thirds of the measure of inequality. The change in this variable is also large, for mammography it goes from 20% in 2003 to 70% in 2013, and for cervical screening, from just over 15% in 2003 to 67% in 2013. Finally, income has diametrically opposite trends in mammography and cervical screening. In the first, the decomposition shows it is becoming less important over time, in the latter, exactly the opposite. In any case, by 2013, income contributes to just fewer than 6% and 7% respectively for inequality in mammography and cervical screening. For 2008, for the model that does not include health insurance, the contribution of income to unfair overall inequality in mammography is 38% and 72% respectively.

As discussed below, the results of this research have some potential policy implications, a number of limitations and shortfalls and a few strengths. It however provides unequivocal evidence of existence of overall unfair inequality in health care in Brazil and points to a higher degree of inequality in preventive care, when compared to primary and secondary care (as proxied by the probability of visiting a primary or secondary care physician), and even higher inequality in capital-intensive preventive procedures.

7.2 Policy Implications

Healthcare systems that fail to tackle inequality could potentially suffer undesired consequences, including higher rates of mortality and poor health of individuals in the most deprived groups of society. This, in turn, could provoke extra financial strain on the national healthcare system, as caring for the sick is, in general, more expensive than preventing poor health (Fineberg, 2013, Lozano et al., 2012).

The findings of this thesis have various potential policy implications. To start with, it is clear that social inequality in health care in Brazil is not only and indeed not primarily related to income as opposed to other social variables such as education, region, urban or rural residency and health insurance status. This suggests that some actions should be directed at tackling these other sources of inequality. In terms of region, my models have indicated that the North and North-East regions are worse-off in terms of likelihood of receiving all three forms of care studied (physician visits, mammography and cervical screening). An intervention that increased the supply of care-givers or healthcare equipment in those regions could, therefore, potentially decrease inequality. These regional inequalities are particularly large in the case of mammography screening, a capital-intensive procedure requiring access to costly scanning equipment. Policies can also be directed at improving access to care in rural regions, although this factor is not as important a contributor to inequality as it used to be.

For preventive care for women, education is becoming more important as a contributor to overall inequality over time. This could be due to the fact that poorly educated women have less understanding of the importance of prevention or more complex factors, including actual constraints in terms of time and access (Cookson et al., 2016).Maybe a possible policy action could include educating women, particularly those who have less formal education, about the importance of mammography and cervical screening in cancer prevention. Given that several areas and a high percentage of the population are covered by National Family Health Strategy (PSF), some training could be directed at the healthcare agents, who could convey the knowledge about prevention and, perhaps, effectively integrate the National Policy on Prevention of Breast and Cervical Cancer into the scope of the National Family Health Strategy.

If we understand overall unfair inequality in cervical screening and mammography as an indicator of inequality in preventive care in general, the realisation that inequality is larger in prevention means that there is room for improvement. Prevention can be understood as care before actual sickness, which is normally associated to information and knowledge (Lorant et al., 2002, Fineberg, 2013). Improving the availability and dissemination of information and knowledge about preventive care could be a possible pathway to decreasing inequality in this type of procedures.

Finally, the results from this research could also be informative for public spending decisions. Deprived regions and rural areas could receive some extra funding, in order to facilitate access to care and potentially decrease inequality. Likewise, particular groups which are less likely to receive care could be targeted in campaigns. For example, a campaign could be directed at elderly members of society (60+), as they are less likely to visit physician compared to other adult groups, but could have a higher need for care, as we have demonstrated in Chapters 4 and 6.

Several European nations have applied various methods to tackle inequality within their health systems. In practice, certain methods like changing the geographical resource allocation formula or encouraging the hiring of physicians in more deprived areas of the country through financial incentives are easier to implement, due to their flexibility regarding resources allocation and adherence to the political and managerial agenda of policy makers and decision making bodies (Mackenbach et al., 2003, Dahlgren and Whitehead, 2007). Certain methods, like increasing the supply of capital-intensive machinery to support the delivery of care, as is the case of mammography, would require greater spending of national resources and consequently can be side-lined in a country like Brazil, where resources are limited and the government currently defends cuts in social costs. As cultural and economic constraints bound Brazil, some methods can be applied in due time. Also in Europe, some strategies were only put in place after many decades. For a number of years, smaller steps were taken for decreasing inequalities in their healthcare system (Mackenbach et al., 2003, Dahlgren and Whitehead, 2007). Nonetheless, a common trend was observed: most countries which were successful in reducing inequality in the delivery of care examined the process and pathways of access to care in order to identify possible gaps. Policy recommendations were, in most cases, supported by research and the movement towards policy implementation was achieved with public engagement (Dahlgren and Whitehead, 2007).

7.3 Strengths and Limitations of the Study

The work of this thesis has several strengths. First, the proposed method permits multiple sources of inequality to be combined in the same analysis, allows for comparability to other methods as well as provides information about the importance of each contributing factor to inequality. Second, the Health Care Advantage (HCA) approach is flexible enough to allow for divergent social value judgements about what counts as a fair or unfair determinant of differences in health care utilisation. A diverse range of social variables may be placed in either the “fair” or “unfair” vector of sources of inequality, depending on the objective of the analysis, and sensitivity analysis may be conducted to allow for alternative normative views. Third, the approach can be used to produce a range of inequality measures, including those commonly used in income-related inequality studies, such as the concentration index (CI) or the horizontal inequality index (HI), but also absolute and relative gaps between quintile groups.

Regarding the empirical results presented, the analysis performed has used data that is representative of Brazil at a national and subnational level, and the sample sizes are relative large, with more than 350 thousand individuals in each wave, and information available for comparison for at least 3 years. Still regarding the data, as far as we are aware, this is the first inequality study to incorporate the new wave of data, relating to 2013, but only made public in the second half of 2015. Furthermore, this is also the first study, to our knowledge to analyse inequalities in mammography and cervical screening in detail at a national level.

Regarding the modelling performed, my research only allowed for age, sex and self-assessed health as measures of need, and did not also allow for self-reported chronic conditions due to concerns about the reliability of these particular survey variables due to under-diagnosis and reporting bias (Bago d'Uva et al., 2009). This is a limitation, and further research is needed to understand and potentially correct biases in the reported prevalence of chronic conditions. Cancer and Cirrhosis appear to be particularly skewed and perhaps should be considered priority in terms of future research. There is also scope for policy action directed at increasing diagnosing in lower socio-economic groups for these conditions.

Furthermore, this study has broadened the view on inequality by focusing on overall unfair inequality instead of socio-economic or income-related inequality. This derives from the understanding that several factors might be relevant where inequalities are concerned (Fleurbaey and Schokkaert, 2009), and if equality is to be achieve, all these factors should be taken into consideration. In case of Brazil, it could be reasonably asserted that the overall unfair healthcare inequality is much broader than income-related inequality.

The present research also has numerous limitations. First, as already mentioned, since the research abstains from employment of chronic factors as predictors of healthcare, it avoids potential reporting bias available, but does not correctly adjust for measures of healthcare need. This is particularly relevant for physician visits, as people with higher levels of need should be entitled to more visits. By relying purely on self-assessed health as a measure of need, I may indeed be falling into another reporting bias. As far as need for health care is concerned, I have also assumed in this research that there is no particular genetic endowment related to ethnicity which would increase the need for care of a particular ethnic group. This assumption is fairly common for care in the form of physician visits, but is more debatable in the case of cancer prevention. There are studies that demonstrate a higher likelihood of black women developing cancer in the USA (Mandelblatt et al., 1991, Li et al., 2003), but no such information for Brazil. Thus, for the purposes of inequality measure, ethnicity was considered an unfair source of inequality. This may imply that I am overestimating the measure of overall unfair inequality, by deeming unfair a factor that may in reality be a fair source of inequality.

Another important limitation of the present study relates to the fact that, although the decrease in overall unfair inequality in Brazil is simultaneous to the expansion of the National Family Health Strategy (Programa Saúde da Família - PSF) and the establishment of the National Policy on Prevention of Breast and Cervical Cancer, the work of this thesis does not establish a direct relationship between the national strategy and policy and inequality observed.

Direct comparison of most of the results of this study to international literature is limited for a number of reasons. As already mentioned, the method proposed allows for the comparison in principle between income-related and overall unfair inequality. However, comparability is limited because i) this is the first study to use an overall measure of unfair inequality in health care and incorporate other variables into the vector of unfair determinants of health care; other studies have examined factors other than socio-economic related inequality but have not combined them into a single over-arching index (Almeida et al., 2013, Devaux and De Looper, 2012, Bago d'Uva et al., 2009, Van Doorslaer et al., 2006, van Doorslaer et al., 2000, Suárez-Berenguela, 2000, van Doorslaer et al., 1997b, van Doorslaer et al., 1992); ii) Brazil, unlike many high income countries, does not differentiate between GPs and specialists. This second point is less relevant as the same is found in most countries in Latin America and the Caribbean (Suárez-Berenguela, 2000) Even where income-related inequality has been reported throughout this thesis, comparability with international literature is not always possible. For the case of physician visits, this derives from the fact that the survey used does not differentiate between general practitioners, family doctors and specialists, as is often the case in high-income countries based studies. Last but not least, several inequality studies that focus on cancer screening for women do not use summary measures which take account of all parts of the distribution, such as the concentration index or the horizontal inequity index (Palencia et al., 2010, Moser et al., 2009, Couture et al., 2008, Lorant et al., 2002).

Finally, as discussed in the Introduction, the most important limitation of this thesis is that the methods applied and results obtained do not allow for causal inference. The thesis provides a measure of overall unfair inequality, and an indication of the importance of different social factors in contributing to overall unfair inequality, but does not provide information about the causes of unfair inequality. Furthermore, social value judgements about how far different social variables are "fair" or "unfair" determinants of inequality partly depend on empirical assumptions about causal pathways. For example, how far health insurance status is considered to be an "unfair" determinant of an individual's health care utilisation may depend on empirical assumptions about how far health insurance status in adulthood is determined by childhood circumstances for which the individual cannot be held responsible. So lack of clear evidence about causal pathways means that both the overall measure of unfair inequality and the decomposition of the importance of different factors are subject to uncertainty and bias. I have attempted to address this issue by conducting a form of sensitivity analysis, when looking at decomposition, which could provide some insight regarding different assumptions about "fair" and "unfair" variables, but the lack of structural modelling of the causal pathways is clearly an important limitation of this research, and indeed of almost all previous work in this area, and is an important avenue for future research.

7.4 Future Research: some suggestions

The research here presented leaves room for several new research questions and investigation proposals. To start with, the Health Care Advantage (HCA) approach could be applied to other countries and provide evidence in terms of overall unfair inequality that would be comparable to the ones demonstrated in my analysis. The HCA approach could also be applied to other relevant forms of care in Brazil, and perhaps one could use the proposed approach to try to explain inequalities in chronic conditions. If there is under-diagnosis in the poorer segments of the population, one would expect overall unfair inequality to be large and income to be one of the most important contributors to that inequality. In any case, applying the HCA approach to chronic conditions as a measure of health would consist of an innovative application, as focused on health instead of healthcare, and could be informative of underlying aspects of inequality; although, the causal inference limitation would still apply.

Another interesting avenue for future research relates to the investigation of capital-intensive *versus* labour-intensive forms of health care. It would be interesting in overall unfair inequality could be calculated for a range of preventive and non-preventive capital-intensive procedures and labour-intensive procedures. This could provide a somewhat systematic indication of how important the nature of the procedure is, as far as inequality is concerned and may provide indications about the physical supply of care and inequality.

A third possibility of future research would look at possible implications and applications of the Health Care Advantage (HCA) approach and public spending and budget allocation. This approach, given its nature, could be used to allocate resources into the healthcare system, and potentially decrease inequality by improving allocation.

Another possibility for future research would be to examine whether there is a causal relationship between the National Policy on Prevention of Breast and Cervical Cancer and National Family Health Strategy (PSF) and the decrease in inequality observed in the time period of analysis. Given that the policies were implemented gradually across different locations, one could try a difference-in-difference approach using areas where policy was still not in effect at the time as a control group. Even if one finds that a difference-in-difference approach is not suitable, due to the lack of a clear time and location of the intervention, maybe parameters could be set in terms of population coverage overtime and how inequality has changed. Particularly for physician visits, there is information for 2008 and 2013 whether the care received fell under the National Family Health Strategy. Therefore, it would be possible to evaluate how overall unfair inequality has changed for the group covered under the strategy and how this compares to inequality within the population not (yet) covered by the strategy.

Finally, future research should try to go beyond the current limitations of this thesis. Perhaps the most prominent limitation to overcome is the lack of causal inference, both to understand the causes of health care inequality and to make more informed and nuanced value judgements about what counts as fair and unfair inequality. Hence, structural modelling that can help to untangle the causal pathways between different social variables and the utilisation of health care would be useful and informative for addressing health care inequalities.

APPENDICES

Appendix A: Appendix to Chapter 4

Table A1 – logit standardising regression results for physician visits

	Basic		Intermediate		Comprehensive	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
Intercept	0.773	0.040	0.674	0.071	0.595	0.099
Equivalised household income in 000s of Brazilian real (ln)	1.396	0.021	1.246	0.022	1.090	0.024
<u>**NEED FACTORS**</u>						
Male (base)						
Female	2.382	0.063	2.341	0.063	2.434	0.077
Age group (base: younger than 15 years of age)						
15 - 29	0.865	0.054	0.656	0.046	0.765	0.077
30 - 44	1.056	0.069	0.852	0.051	0.928	0.101
45 - 60	1.136	0.072	0.990	0.095	1.003	0.086
60 +	1.474	0.098	1.156	0.140	1.294	0.179
Self-Assessed Health (base: Very Good Health)						
Good	1.304	0.042	1.374	0.045	1.440	0.053
Regular	2.844	0.131	3.252	0.153	3.633	0.195
Bad	6.561	0.756	8.147	0.953	10.205	1.073
Very Bad	5.894	1.326	6.978	1.604	10.893	2.639
<u>**NON - NEED FACTORS**</u>						
Educational Achievement (base: no education)						
Incomplete Primary			1.118	0.053	1.030	0.058
Primary			1.237	0.079	1.072	0.079
Incomplete Secondary			1.242	0.088	1.057	0.086
Secondary			1.574	0.092	1.263	0.085
Incomplete Higher			1.572	0.144	1.172	0.119
Higher			2.029	0.169	1.415	0.131
Undetermined			1.841	0.480	1.748	0.502
Region (base: North)						
North East			1.205	0.055	1.115	0.059
South East			1.516	0.071	1.312	0.071
South			1.249	0.067	1.131	0.070
Centre West			1.215	0.065	1.108	0.068
Urban (base)						
Rural					0.823	0.035

Table A1 – logit standardising regression results for physician visits

(continued)

	Basic		Intermediate		Comprehensive	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
<u>**NON - NEED FACTORS (continued)**</u>						
Ethinicty (base: white)						
Native					1.178	0.192
Black					1.221	0.108
Asian					1.043	0.244
Mixed					1.152	0.086
Undetermined					0.186	0.113
Emplyment Status (base: occupied)						
Unoccupied					1.040	0.043
Family Type (base: no children)						
children under 14					0.743	0.041
children 14+					1.167	0.115
Health Insurance (base: No)						
Yes					2.070	0.088
Seatbelt Preference (base: always)						
Doesn't ride in front seat					1.057	0.057
Often					0.862	0.075
Sometimes					0.987	0.072
Rarely					0.770	0.058
Never					0.826	0.054
Adjusted R-squared		0.0849		0.093 7		0.1153
Number of observations		34624		34624		28067

Appendix B: Appendix to Chapter 5

Table B1 – logit standardising regression results for mammography

	Basic		Intermediate		Comprehensive	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
Intercept	0.196	0.016	0.064	0.030	0.090	0.047
ln(income)	2.080	0.065	1.725	0.067	1.430	0.064
<u>NEED FACTORS</u>						
Age group (base: between 15 and 25 years of age)						
25 - 29	1.381	0.158	1.411	0.160	1.336	0.169
30 - 34	2.081	0.230	2.250	0.250	2.162	0.270
35 - 39	3.069	0.326	3.415	0.363	3.202	0.386
40 - 44	3.677	0.390	4.427	0.478	4.236	0.520
45 - 49	3.894	0.427	5.010	0.562	4.681	0.602
50 - 54	3.710	0.439	5.001	0.610	4.706	0.673
55 - 59	2.981	0.375	4.258	0.562	4.112	0.633
60 - 64	1.887	0.267	2.790	0.412	2.201	0.379
65 - 69	1.317	0.229	1.925	0.346	1.705	0.351
70 +	1.130	0.229	1.760	0.362	1.692	0.397
<u>NON - NEED FACTORS</u>						
Educational Achievement (base: no education)						
Incomplete Primary			1.408	0.134	1.225	0.139
Primary			1.872	0.225	1.527	0.217
Incomplete Secondary			1.684	0.266	1.381	0.252
Secondary			2.522	0.266	1.732	0.222
Incomplete Higher			3.544	0.576	2.295	0.417
Higher			2.654	0.348	1.665	0.253
Undetermined			2.279	0.769	1.539	0.606
Region (base: North)						
North East			1.168	0.116	1.1060	0.131
South East			2.190	0.212	1.7100	0.201
South			1.495	0.159	1.2009	0.156
Centre West			1.417	0.160	1.3217	0.173
Urban (base)						
Rural					0.9345	0.014

Table B1 – logit standardising regression results for mammography

(continued)

	Basic		Intermediate		Comprehensive	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
<u>NON - NEED FACTORS (continued)</u>						
Ethinicty (base: white)						
Native					0.9301	0.162
Black					0.9499	0.112
Asian					1.0556	0.232
Mixed					0.9516	0.072
Emplyment Status (base: occupied)						
Unoccupied					0.9710	0.063
-						
Family Type (base: no children)						
children under 14					0.904	0.107
children 14+					1.072	0.071
Health Insurance (base: No)						
Yes					2.119	0.144
Seatbelt Preference (base: always)						
Doesn't ride in front seat					1.309	0.153
Often					0.708	0.129
Sometimes					0.804	0.109
Rarely					0.868	0.119
Never					0.835	0.122
Adjusted R-squared		0.085		0.108		0.137
Number of observations		11028		11028		9005

Table B2 – logit standardising regression results for cervical screening

	Basic		Intermediate		Comprehensive	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
Intercept	1.270	0.072	1.098	0.441	1.017	0.487
ln(income)	1.493	0.038	1.346	0.043	1.187	0.044
<u>NEED FACTORS</u>						
Age group (base: younger than 25 years of age)						
25 - 29	1.154	0.092	1.197	0.097	1.201	0.108
30 - 34	1.035	0.084	1.104	0.091	1.137	0.108
35 - 39	1.063	0.086	1.150	0.095	1.215	0.101
40 - 44	0.880	0.073	1.001	0.085	1.140	0.103
45 - 49	0.900	0.079	1.067	0.097	1.278	0.107
50 - 54	0.748	0.072	0.923	0.093	1.088	0.110
55 - 59	0.549	0.059	0.710	0.079	0.886	0.085
60 - 64	0.390	0.046	0.523	0.064	0.569	0.082
65 - 69	0.260	0.038	0.356	0.054	0.428	0.077
70 +	0.164	0.031	0.233	0.045	0.281	0.062
<u>NON - NEED FACTORS</u>						
Educational Achievement (base: no education)						
Incomplete Primary			1.413	0.108	1.249	0.113
Primary			1.626	0.162	1.464	0.172
Incomplete Secondary			1.577	0.199	1.325	0.193
Secondary			2.088	0.180	1.632	0.169
Incomplete Higher			2.488	0.360	1.845	0.295
Higher			2.105	0.238	1.468	0.191
Undetermined			2.694	0.856	3.215	1.232
Region (base: North)						
North East			1.070	0.083	1.042	0.096
South East			1.185	0.091	1.012	0.094
South			1.074	0.092	0.960	0.101
Centre West			1.173	0.106	1.110	0.118
Urban (base)						
Rural					0.958	0.072

Table B2 – logit standardising regression results for cervical screening

(continued)

	Basic		Intermediate		Comprehensive	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
<u>NON - NEED FACTORS (continued)</u>						
Ethinicty (base: white)						
Native					0.519	0.272
Black					0.630	0.335
Asian					0.551	0.352
Mixed					0.567	0.297
Emplyment Status (base: occupied)						
Unoccupied					1.214	0.047
Family Type (base: no children)						
children under 14					0.813	0.177
children 14+					1.236	0.314
Health Insurance (base: No)						
Yes					1.963	0.125
Seatbelt Preference (base: always)						
Doesn't ride in front seat					1.213	0.112
Often					0.768	0.114
Sometimes					0.976	0.127
Rarely					0.925	0.123
Never					0.955	0.112
Adjusted R-squared		0.044		0.053		0.071
Number of observations		11028		11028		9005

Appendix C: Appendix to Chapter 6

Table C1 – logit standardising regression results for physician visits

	1998		2003		2008		2013	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**	**odds ratio**	**se**
Intercept	0.368	0.282	0.909	0.252	0.333	0.035	0.697	0.124
ln(income)	1.003	0.000	1.016	0.045	1.081	0.018	1.026	0.028
<u>NEED FACTORS</u>								
Male (base)								
Female	1.801	0.145	2.001	0.051	2.577	0.081	2.389	0.168
Age group (base: younger than 15 years of age)								
15 - 29	1.087	0.042	1.209	0.043	0.916	0.066	1.071	0.096
30 - 44	1.453	0.244	1.445	0.062	1.322	0.093	1.243	0.128
45 - 60	2.444	0.423	1.815	0.809	1.627	0.132	2.268	0.302
60 +	3.077	0.094	2.062	0.218	2.080	0.235	2.364	0.323
Self-Assessed Health (base: Very Good Health)								
Good	1.630	0.140	1.294	0.039	1.399	0.054	1.233	0.112
Regular	1.877	0.789	3.207	0.137	3.474	0.187	2.759	0.337
Bad	4.444	0.642	5.679	0.555	7.678	1.891	6.370	0.889
Very Bad	5.475	6.176	6.147	1.404	8.725	1.080	11.003	1.548
<u>NON - NEED FACTORS</u>								
Educational Achievement (base: no education)								
Primary	0.640	0.182	0.608	0.136	1.072	0.079	0.802	0.109
Secondary	0.858	0.234	0.612	0.047	1.263	0.085	1.028	0.162
Incomplete Higher	1.052	0.376	0.656	0.053	1.172	0.119	0.883	0.166
Higher	1.086	0.298	1.077	0.266	1.415	0.131	1.017	0.141
Undetermined	1.364	0.402	0.785	0.076	1.748	0.502	1.167	0.224
Region (base: North)								
North East	1.154	0.163	0.923	0.039	1.115	0.059	1.222	0.202
South East	1.200	0.196	1.142	0.050	1.312	0.071	1.568	0.190
South	1.161	0.190	1.035	0.052	1.131	0.070	1.413	0.167
Centre West	1.079	0.155	1.022	0.052	1.108	0.068	1.096	0.112
Urban (base)								
Rural	0.776	0.092	0.703	0.024	0.823	0.035	0.910	0.113

Table C1 – logit standardising regression results for physician visits

(continued)

	1998		2003		2008		2013	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**	**odds ratio**	**se**
<u>NON - NEED FACTORS (continued)</u>								
Ethinicty (base: white)								
Native	0.953	0.638	0.651	0.176	0.915	0.303	0.822	0.108
Black	0.953	0.656	0.558	0.153	0.694	0.173	0.883	0.274
Asian	2.456	2.819	1.420	0.150	1.046	0.065	1.176	0.589
Mixed	0.901	0.605	0.619	0.167	0.994	0.035	0.938	0.078
Employment Status (base: occupied)								
Unoccupied	1.216	0.101	1.114	0.033	1.144	0.083	1.089	0.067
Family Type (base: no children)								
children under 14	0.756	0.169	0.757	0.047	0.837	0.057	0.871	0.102
children 14+	1.319	0.323	1.036	0.054	1.070	0.062	1.018	0.113
Health Insurance (base: No)								
Yes	2.503	0.236	2.831	0.097	2.893	0.092	3.803	0.317
Adjusted R-squared		0.110		0.099		0.119		0.127
Number of observations		33533		38351		39871		40186

Table C2 – logit standardising regression results for mammography

	2003		2008		2013	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
Intercept	0.018	0.015	0.067	0.035	0.388	0.142
ln(income)	1.003	0.001	1.154	0.028	1.033	0.057
NEED FACTORS						
Age group (base: younger than 25 years of age)						
25 - 39	1.988	0.100	2.094	0.171	1.305	0.153
40 - 49	3.126	0.134	4.330	0.167	1.331	0.147
50 - 60	1.841	0.128	2.227	0.268	1.237	0.134
60 +	1.033	0.384	1.327	0.191	0.751	0.130
NON - NEED FACTORS						
Educational Achievement (base: no education)						
Primary	1.774	0.200	1.350	0.133	1.229	0.131
Secondary	1.469	0.198	1.781	0.104	1.408	0.121
Incomplete Higher	2.364	0.143	2.006	0.160	1.617	0.119
Higher	1.840	0.109	1.624	0.130	1.625	0.275
Undetermined	2.243	0.282	2.078	0.247	1.949	0.209
Region (base: North)						
North East	1.422	0.153	1.153	0.124	1.158	0.174
South East	2.168	0.230	1.865	0.200	1.446	0.192
South	1.353	0.161	1.408	0.167	1.335	0.174
Centre West	1.760	0.211	1.320	0.161	0.940	0.081
Urban (base)						
Rural	0.856	0.063	0.647	0.062	1.079	0.205

Table C2 – logit standardising regression results for mammography

(continued)

	2003		2008		2013	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
<u>**NON - NEED FACTORS (continued)**</u>						
Ethinicty (base: white)						
Native	0.623	0.096	0.943	0.064	0.892	0.110
Black	0.754	0.063	0.855	0.073	0.612	0.057
Asian	0.814	0.060	0.934	0.166	1.421	0.082
Mixed	0.694	0.204	0.924	0.154	0.917	0.053
Emplyment Status (base: occupied)						
Unoccupied	1.036	0.062	0.799	0.119	0.924	0.099
Family Type (base: no children)						
children under 14	0.684	0.072	0.736	0.076	0.935	0.135
children 14+	1.298	0.117	1.059	0.529	1.176	0.096
Health Insurance (base: No)						
Yes	2.907	0.168	2.280	0.152	2.515	0.267
Adjusted R-squared		0.126		0.129		0.109
Number of observations		10703		14214		12669

Table C3 – logit standardising regression results for cervical screening

	2003		2008		2013	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
Intercept	1.719	0.142	0.818	0.082	0.349	0.067
Equivalised household income in 000s of Brazilian real	1.004	0.003	1.079	0.024	1.025	0.056
NEED FACTORS						
Age group (base: younger than 25 years of age)						
25 - 39	1.293	0.103	1.180	0.113	1.603	0.162
40 - 49	1.068	0.098	1.201	0.116	1.569	0.103
50 - 60	0.447	0.046	0.565	0.076	0.971	0.102
60 +	0.180	0.026	0.239	0.048	0.463	0.090
NON - NEED FACTORS						
Educational Achievement (base: no education)						
Primary	1.312	0.168	1.250	0.175	1.217	0.077
Secondary	1.384	0.193	1.825	0.171	1.221	0.107
Incomplete Higher	2.274	0.202	1.970	0.211	1.473	0.117
Higher	1.174	0.119	1.607	0.197	2.192	0.156
Undetermined	1.231	0.154	1.292	0.103	1.162	0.143
Region (base: North)						
North East	1.090	0.097	1.019	0.086	1.124	0.111
South East	1.334	0.121	1.078	0.092	1.252	0.161
South	1.163	0.121	1.017	0.098	0.985	0.115
Centre West	1.340	0.143	1.108	0.109	1.307	0.170
Urban (base)						
Rural	0.486	0.034	0.911	0.063	0.866	0.067

Table C3 – logit standardising regression results for cervical screening

(continued)

	2003		2008		2013	
	odds ratio	**se**	**odds ratio**	**se**	**odds ratio**	**se**
<u>**NON - NEED FACTORS (continued)**</u>						
Ethinicty (base: white)						
Native	0.498	0.030	0.684	0.080	0.873	0.072
Black	0.892	0.093	0.799	0.067	0.695	0.083
Asian	0.922	0.089	0.742	0.032	0.919	0.090
Mixed	0.848	0.054	0.727	0.028	0.986	0.159
Emplyment Status (base: occupied)						
Unoccupied	1.254	0.068	1.215	0.148	1.149	0.147
Family Type (base: no children)						
children under 14	0.806	0.077	0.643	0.057	0.962	0.109
children 14+	1.023	0.132	0.899	0.122	1.030	0.149
Health Insurance (base: No)						
Yes	2.821	0.192	2.018	0.126	2.507	0.191
Adjusted R-squared		0.117		0.075		0.080
Number of observations		10709		10056		9301

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