AN ECONOMIC ANALYSIS OF VERTICAL EQUITY IN THE DELIVERY OF HEALTH CARE IN ENGLAND

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A thesis submitted for the degree of Doctor of Philosophy

UCL

DECLARATION

I, Laura Vallejo-Torres, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

PUBLICATIONS

Published papers

At the time of submission of this thesis two papers consisting of a substantial part of Chapter 2 and Chapter 3 have been published:

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Invited book chapter

A papers related to Chapter 4 is being prepared for publication as a book chapter in the on-line Encyclopaedia of Health Economics; Ed. Culyer, A; Elsevier

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Papers under review

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CONFERENCE PRESENTATIONS

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ABSTRACT

In this thesis we examine the overlooked issue of vertical equity in health care delivery. This principle requires that individuals with unequal needs receive appropriately unequal treatment. Most analyses of equity in health care delivery focus only on horizontal equity, i.e. the principle of equal treatment for equal needs. Therefore, the aim of this thesis is to assess and refine the techniques to investigate vertical inequity, and to offer evidence about vertical equity in the English health care system. The extent of inequalities in health is first investigated. We find persistent inequalities in health in England. We then illustrate the methods widely used in the literature to explore horizontal inequity in health care and highlight a major limitation; these studies ignore the possibility that the estimated differential treatment received by individuals with different needs is inappropriate. In order to identify the methods used to date to measure vertical equity we review the empirical literature. The most comprehensive techniques identified focused on the socioeconomic dimension of vertical inequity. We illustrate these techniques and suggest an extension to this measure that takes into account the full distribution of needs in a population. We apply our suggested methods to measure inequity in individual level and in area level health care provision in England. The optimal variation of health care with variation in needs is estimated based on subgroups less likely to be affected by unmet needs. The findings of this thesis indicate that there is vertical inequity in detriment to socioeconomic deprived groups and, to a larger extent, in detriment to those with larger needs. We show that including vertical inequity aspects may lead us to draw different conclusions about the nature and extent of inequity. Therefore, conclusions about inequities in health care are extensively being made on the basis of incomplete information.

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CHAPTER 1

Introduction

1.1. Background

Tackling inequity is a primary aim in the English National Health Service (NHS). While England is now healthier than ever, inequalities in health in the population are found to persist (Department of Health, 2008a). The size of the problem has been investigated by a number of Government-commissioned reports such the Black Report, 1980; the Acheson Report, 1998; and the Marmot Review, 2010. These documents have all reached the same conclusions, highlighting the persisting inequalities in health that remain even in the context of a publicly-funded, universal, and free at the point of delivery, health care system such as the one introduced in the United Kingdom in 1948.

Substantial efforts have been diverted to address these inequalities in health. The policy commitment of reducing health inequalities in the population has become even more explicit in the past years. Health inequalities targets were announced in 2001 by the Government, which concentrated in reducing by at least 10 per cent the existing gap between socioeconomic groups in infant mortality; and the gap between areas with the lowest life expectancy at birth and highest deprivation and the population as a whole by 2010. These targets were not achieved, and further efforts have been devoted at finding the best evidence-based ways of reducing health inequalities.

The most recent of the mentioned reports, Fair Society, Healthy Lives, 2010 chaired by Sir Michael Marmot consists of a strategic review aimed at informing on ways to reduce health inequalities. The primary aim of the review was the social gradient observed in health. The document highlights the substantial socioeconomic inequalities in health still seen in England, e.g., people living in the poorest neighbourhoods, will, on average, die seven years earlier than people living in the richest neighbourhoods; the average difference across rich/poor neighbourhoods in disability-free life expectancy is found to be 17 years.

The socioeconomic dimension of health inequalities is often chosen to be the outcome of analysis of inequalities in health. Inequalities in health are thus commonly investigated with respect to a socioeconomic indicator in order to measure the gap in health status between those at the top and bottom ends of the socioeconomic scale. Alternatively, some have advocated for the analysis of inequalities in health that also consider other sources of inequalities and suggest focusing on the analysis of total health inequalities (Gakidou *et al.*, 2000). Policy makers' views appear to share a commitment for the reduction of both, total and socioeconomic-related inequalities in health. The Government 2001 targets summarised above are an example. While the first objective related to targeting infant mortality variations across socioeconomic groups, the second specified target was mainly concerned with overall variation in life expectancy at birth across regions. In empirical research, whether the measurement of inequalities should account for all inequalities, or only for those inequalities systematically associated with socioeconomic factors appears to be a long-standing issue (Bleichrodt & van Doorslaer, 2006).

In addition to this issue, there is also some debate around the justification for the consideration of inequities in the delivery[1] of health care. Some have argued that the distribution of health care matters only to the extent in which it affects the ultimate goal of a desired distribution of health (Culyer & Wagstaff, 1993). This is related to the view that what makes health a special entity is that health is necessary for the individual to "flourish" as a human being (Wiggins, 1984). Therefore, according to some authors the ethical justification for being concerned with the distribution of medical care is that it contributes to improve health.

However, it is generally understood that the role of health care in determining health is relatively limited. This fact has not nevertheless led policy makers to abandon concerns about achieving an equitable distribution of health services. In fact, equity in the delivery of health care is an important policy objective in many health care systems. The emphasis on equity in health care allocation may be partly because health care delivery is still one of the determinants of health subject to policy control. In addition, it might be that achieving equity in the distribution of health services is seen as an aim in its own right, over and

[1] The term "delivery" of health care is used throughout this thesis to refer to utilisation of, access to, and resource allocation of health care

above its impact on the distribution of health. In any case, many health care systems including the UK distribute health care resources on the basis of explicit equity objectives. Such objectives often subscribe to egalitarian goals, which suggest that health care should be distributed according to 'need' and finance according to ability to pay (Wagstaff & van Doorslaer, 2000).

Egalitarian goals can include horizontal and/or vertical equity principles. These Aristotelian principles of inequity are defined as follows. The horizontal equity principle requires that individuals with the same needs receive the same treatment. The vertical equity principle requires that those with different needs receive appropriately different care. Taken together, these principles suggest not only that patients with the same health status should receive the same treatment irrespective of, for instance, their social class or place of residence, but also that those suffering from worse ill health should be properly prioritised in receiving health care. Most of the attention to date has been limited to the principle of horizontal inequity.

To illustrate the difference between horizontal and vertical inequity, Table 1.1 provides a hypothetical example of the allocation of GP visits in a population with four individuals, two of them with good health and two of them with poor health.

Table 1.1. Illustration of vertically and horizontally equitable allocations of GP visits

Person	Health	GP Visits				
		A	B	C	D	E
1	Good	10	10	10	10	10
2	Good	15	10	15	10	10
3	Poor	10	20	20	10	15
4	Poor	15	20	30	10	15
Horizontal		Inequity	Equity	Inequity	Equity	Equity
Vertical		Inequity	Equity	Equity	Inequity	Inequity

The horizontal equity principle requires that individuals with the same needs receive the same treatment, i.e. those with good level of health should have the same number of GP visits and those with poor level of health should have the same number of GP visits. Therefore, allocations A and C are not horizontally equitable as individuals with the same health status receive different levels of health care. Note than even in the situation where everyone receives the same care independently of their health, i.e. as defined by allocation D, the situation meets the horizontal equity principle. The vertical equity principle requires that individuals with different needs receive appropriately unequal treatment. Finding the appropriate way in which health care consumption ought to vary with variations in needs is one of the main challenges of vertical equity analyses. For the sake of this example, we assume that individuals in poor health need twice as many GP visits as those in good health. In that case, allocations B and C meet the vertical equity requirement, as in both cases individuals in poor health receive, on average, double the number of GP visits as compared with the healthy[2]. The only allocation meeting both vertical and horizontal equity principles is the allocation defined by B. Therefore, analyses that focus only on horizontal inequity will consider situation E, and even situation D to be equitable, ignoring the fact that sick individuals are not receiving as much health care as they need compared with those who are relatively healthier.

Despite the fact that vertical inequity aspects are known to be part of the inequity that may be present in a health care system, the majority of empirical research has focused solely on the horizontal equity principle, by exploring deviation of this principle with respect to a measure of socioeconomic status. There are probably two main reasons for the limitation to socioeconomic-related horizontal inequity considerations in the literature. The first is that in most countries, including the members of the Organization for Economic Cooperation and Development (OECD), the aim to ensure equitable access to health care has often been interpreted as requiring that care ought to be available on the basis of needs and not on the basis of willingness or ability to pay (van Doorslaer *et al.*, 2006). Specifically in the UK, the explicit equity objective guiding health care delivery has traditionally been based on the principle of horizontal equity. For example, in the NHS in England from 1976-1989 the Resource Allocating Working Party (RAWP) Formula was used to allocate Hospital and Community Health Services resources. The equity principle underpinning the RAWP Formula was 'equal opportunity of access to health care for people at equal risk' (Department of Health, 1999) and this principle persists to the present in English resource allocation formulae. However, in more recent times there has been a growing interest in other equity goals. For example, since 1999 a second equity objective

[2] Note that situation C meets the vertical equity principle if the definition of equity is consistent with a view that focus on what happen on average in a population.

has also been pursued in England – to contribute to the reduction of avoidable health inequalities – which from 2001/02 was to be considered jointly with the equal opportunity of access objective in the development of the English resource allocation formulae (Department of Health, 2008b).

Explicitly introducing the aim of reducing health inequalities in the allocation of health care resources has emphasised the role of vertical equity. Rice and Smith, 2001 specifically linked the principle of vertical equity in health care with the objective of achieving equal health outcomes, while they considered horizontal inequity to embodied solely the objective of equal access. Hauck *et al.*, 2002 have also argued that accounting for vertical equity could address inequalities in health that will otherwise not be addressed by ensuring only horizontal equity. The reason is that even when individuals with equal needs are treated equally inequalities in health arise due to the differences in their health production functions, and that addressing those '[...] *implies a desire to move away from a policy of equality of access (horizontal equity) towards one of targeting health care at particular classes of individual (vertical equity)'*. Interestingly, the Marmot Review, 2010 concludes that in order to reduce the steepness of the social gradient in health, *"actions must be universal, but with a scale and intensity that is proportionate to the level of disadvantage".* The authors call this principle *proportionate universalism*. It is quite straightforward to see the similarities of this principle with the Aristotelian principle of vertical equity. Outside the UK there is also a move towards the emphasis on vertical equity. When advocating to reduce the health gap that exists for particularly disadvantaged groups, Mooney, 2008 has claimed that the notion of horizontal equity is not relevant when dealing with individuals with substantial differences in health status. Therefore, all these arguments seem to highlight the importance of moving towards vertical equity considerations in order to achieve the goal of reducing avoidable inequalities in health.

The second factor explaining the lack of empirical research on vertical equity relates to the strong value judgments that are required for its assessment (Gravelle *et al.* 2006). In order to explore vertical equity researchers have to compare the actual variation of care between need groups with the *target* variation of care between need groups. Given the difficulties in defining such a target, analyses are often limited to assessing horizontal inequity in health service delivery. However, a major limitation of this approach is that it ignores the possibility that the estimated differential treatment received by individuals with different needs is inappropriate, i.e., vertical inequity aspects. In empirical analysis of horizontal inequity, this underlying assumption has been summarised as '*on average the system gets it right'* (van Doorslaer *et al*., 2000).

The major implication of assuming that the system is on average currently meeting the needs of the population is that existing inequities due to unmet needs would be perpetuated (Smith, 2008). This has led to tentative investigations of including a vertical equity adjustment on the way health care resources are geographically allocated in countries where there are specific population groups with very different health status and health care needs than the average population, i.e. the Aborigines in Australia (Mooney *et al*., 2002; Mooney & Henry, 2004); or who have been historically disadvantaged, such as race groups in South Africa (McIntyre & Gilson, 2000; McIntyre & Gilson 2002; McIntyre *et al*., 2002). Sutton and Lock, 2000 have also explored including a vertical equity adjustment in the way health care resource are allocated across areas in Scotland. In recent reviews of the formula used to distribute NHS resources in England there have been some attempts to estimate the optimal magnitude of variations in resources with respect to variations in the need indicators, as opposed to use the estimated variation recovered from the regression analyses used to derive the formulae (Sutton *et al.*, 2002; Morris *et al.*, 2007). The main challenge faced in these attempts has been the identification of the appropriate impact, or weight, of the need indicators to achieve a vertically equitable allocation.

1.2. Research aims

As highlighted above, the principle of vertical equity seems to be gaining momentum in the context of addressing inequalities and inequities in health and health care delivery. However, analyses of vertical equity are rarely undertaken and only very few studies have attempted to include considerations of this principle. Therefore, in an attempt to remedy this situation the aim of this thesis is to provide a rigorous and quantitative analysis of vertical equity in the delivery of health care. The substantial methodological challenges of the measurement of vertical equity and the limited attention paid to vertical inequities in the literature imply the need for the assessment and refinement of the existing techniques for the quantification of vertical inequity. We proposed to extend the inequity measures available and apply a variety of econometric techniques to address these issues. The methodology is then applied to different sets of data covering individual level information on health care utilisation as well as area level data on health care spending. The purpose is to offer evidence of the extent of vertical inequity within the contexts in which inequities in health care delivery are commonly investigated.

We begin our analysis by illustrating the size of the problem regarding inequalities in health over time and across regions in England. We explore both income-related inequality in health and total inequality in health in England using the concentration index and the Gini index approach, respectively. In order to explore trends over time and area variation, we use information from nine years of data (1998-2006) and compute the indices separately for the nine Government Office Regions (GOR) in England. We find significant total inequality in health and income-related inequality in health in every period and in every area of England. Indices of income-related inequalities were found to remain relatively constant over the period of study, while overall inequality appears to be slowly decreasing. The extent of health inequality (both in terms of income-related and total inequality) was found to vary between regions, showing a North-South gradient which have been previously reported in the literature both in terms of deprivation and health status. Furthermore, in the case of income-related inequalities, areas with relatively high level of inequality at the initial period experienced the largest increases in inequality over time. Therefore, this chapter illustrates that the persistent health inequalities in England remain large and in some areas, particularly in the most deprived regions, they continue to widen.

Before a thorough analysis of vertical equity in the delivery of health care may proceed we illustrate the methods commonly used for the analysis of horizontal inequity in the literature and highlight the main limitations of focusing solely on horizontal inequity in Chapter 3. In order to do so, we explore horizontal inequity in primary care services in England. The underpinning assumptions imposed by horizontal inequity investigations with respect to the impact of the indicators that ought to affect health care consumption are exposed. The results from this study also help to highlight that a careful consideration regarding the optimal variation in health care use with respect to variation in morbidity indicators is necessary in order to draw conclusions about vertical equity. An additional contribution with respect to the literature on horizontal inequity in primary care services is that, unlike previous studies which focus on GP service use only, we consider GP and practice nurse use, and allow these types of use to be correlated using a bivariate probit framework. This allows us to draw more robust conclusions about the extent of horizontal inequity in primary care in England. The result indicates that it is difficult to draw conclusions about the extent of primary care inequity based only on analyses of GP visits because practice nurses and GPs see different types of patients; inequities in the use of one type of care may be offset by the other type of care.

In Chapters 4 to 7 we provide the core of the analysis of vertical equity in health care delivery. In Chapter 4 we conduct a review of the literature in order to identify the empirical methods that have been applied to or proposed for exploring vertical equity in health care delivery. The primary aims of Chapter 4 are first to provide a critical review of the methods employed in the literature to date to investigate vertical equity in the delivery of health care and second to identify which methods are best suited to measuring vertical inequity. The considered shortcomings of available studies are emphasised. Additionally, we also explore the empirical literature in vertical equity in other fields rather than health care delivery and assess the potential of adjusting the methods developed in other areas to measuring vertical equity in health care delivery. The information identified in this search also helps us to form an understanding on what it is known about vertical equity in the delivery of health care.

The findings from this review are used to inform the analyses undertaken in subsequent chapters of the thesis. The search allows us to identify the most comprehensive techniques employed to date in the literature for the measurement of vertical equity. These methods developed by Sutton, 2002 were proposed to account for the consequences of vertical inequity across the socioeconomic distribution. Further work to extend this methodology to ensure that the consequences across the whole need distribution are accounted for is thus considered necessary. Furthermore, identifying alternative ways of estimating the target allocation of health care is also identified as an area of improvement in the measurement of vertical equity.

The aim of Chapter 5 is to measure socioeconomic-related vertical equity in health care utilisation in England using the most comprehensive techniques identified in the literature. We focus on cardiovascular disease (CVD)-related use of health services rather than use for any cause. The focus on CVD allows us to use disease-specific health measures that are more likely to reflect need for the disease-specific health care utilisation (van Doorslaer *et al*., 2006). This analysis also provides a number of extensions to the analysis undertaken by Sutton, 2002. First, we look at utilisation of eight different types of health care contacts and procedures. This allows us to examine whether or not the nature and extent of inequity is different for different types of use, allowing us to draw a full picture of inequity in the health care provided to individuals with CVD conditions. Second, we apply a decomposition approach to the inequity estimates to explain, as well as measure, inequity in health care utilisation. Third, the estimation of the appropriate effect of the need variables required for the assessment of vertical equity is derived by exploring alternatives target functions based on the relationship observed in subgroups of the population less likely to be affected by unmet needs. Additionally, various econometrics techniques are applied in order to reduce unobserved reporting heterogeneity in the need measures as well as to explore potential endogeneity problems between health care utilisation and reported CVD problems.

The findings from Chapter 5 illustrate that concentrating solely on the horizontal inequity assessment offers only a partial view of the extent of income-related inequity and that including vertical inequity estimates may lead us to draw different conclusions about the nature and extent of income-related inequity in health service use. Our results show that after accounting for vertical inequity, in addition to horizontal inequity, services commonly provided in primary care settings are found to be equitably distributed across income groups, while outpatient visits, and specialised procedures (electrical recordings of the heart and heart surgery) are found to be disproportionately concentrated among the rich.

As highlighted in the literature review in Chapter 4, the methodology proposed by Sutton, 2002 only takes into account the socioeconomic dimension of vertical equity. The aim of Chapter 6 is to propose and illustrate an extension to this measure of vertical equity that fully accounts for the variation in needs in a population. This is accomplished by computing the vertical equity estimate using concentration indices with respect to the need rank rather than the socioeconomic rank, i.e. incorporating the need dimension in the investigation of inequity in health care use. We argue that the socioeconomic dimension of vertical inequity would be appropriate if the interest of the analyst is to quantify the extent to which vertical inequity affects the allocation of health care across income groups. However, if the aim of the analysis is to derive a measure of the extent to which individuals with unequal needs receive appropriately different treatment (as vertical equity has extensively been defined) this analysis would be rather limited. The proposed methodology is illustrated and compared with the socioeconomic dimension analysis of inequity conducted in the previous chapter. The extent of vertical inequity was shown to have a much larger degree when the full distribution of needs was taken into account. Looking at the total inequity results (horizontal plus vertical inequity) we find evidence of inequity favouring the relatively healthy in a number of types of health care utilisation among individuals with CVD.

In addition, in Chapter 6 we show that the inclusion of the need dimension to the inequity analysis also allows us to investigate the consequences of the effect of the non-need indicators in the allocation of health care across need groups, i.e. need-related horizontal inequity. This means that we are able to measure the distributional impact of the effect of the non-need variables on the allocation received by need groups. For instance, income might affect health care use and richer individuals tend to be concentrated on healthier groups, therefore the effect of income would tend to benefit those who are relatively healthy. Incorporating the need-related inequity analysis alongside the socioeconomic-related inequity analysis of health care, allows us to measure both horizontal and vertical inequity, and the consequences that each of them has for the population groups identified by the other.

In Chapter 7 we analyse vertical and horizontal inequity in area level allocations of expenditure for cancer across Primary Care Trusts (PCTs) in England using the techniques developed in previous chapters. While inequities at the individual level in health care utilisation have been the focus of extensive empirical analysis, variations in area level health care spending are also a major concern. Furthermore, the focus on area level analysis allows us to test the methods proposed in this thesis in a different setting with particular challenges, and to explore alternative ways of identifying the target variation in care with variation in need indicators.

We use panel information on PCT spending on cancer from 2004/05 to 2008/09 and assemble a dataset of PCT variables from publicly available sources on cancer prevalence and mortality, demographic profiles, deprivation, and health care supply. In addition, we create a cancer-related severity index using information from a household survey. Various econometric specifications are investigated to regress cancer expenditure against the covariates accounting for the longitudinal nature of the data. Vertical and horizontal aspects of inequity are analysed with respect to both the socioeconomic and the need dimension. In order to estimate the appropriate effect of the need indicators on spending, we seek to identify subsamples of PCTs that best meet the need of their population by allocating resources appropriately according to needs. We use a series of indicators that fall into four different categories; i) cancer outcomes, ii) treatment services and prevention, iii) World Class Commissioning scores in relevant competencies, and iv) PCTs that allocate the largest amount of resources to the neediest areas. Similarly to the individual level analysis, the extent of vertical equity is much larger with respect to the need dimension than with respect to the socioeconomic dimension. Our findings also indicate that cancer spending might be disproportionally concentrated on poorer areas, while it is also disproportionally concentrated on healthier regions.

Chapter 8 concludes by pulling together the findings of the previous six chapters. We also discuss some research and policy implications of the analysis. We focus on the implications for policy design of addressing vertical inequity in health care delivery; the implications of the emphasis on the need dimension in addition to the socioeconomic dimension when designing policies aimed to tackling inequities in health and health care delivery; and the barriers to services provided in secondary care. We finally discuss some study limitations and offer some suggestions for future research.

1.3. Main contributions

We noted at the outset that very little research has been undertaken to explore vertical inequities in the distribution of health care. This thesis makes an original contribution to the literature in four major respects. First, in Chapter 4 we conduct a review of the literature on vertical equity in the delivery of health care as well as in other fields. To our knowledge, no previous review has been published that covers vertical equity in health care delivery, and so this chapter provides the first review on this topic. Second, in Chapter 6 we show that by focusing on the need dimension in the analysis of vertical inequity we are capable of capturing the extent to which individuals with different needs do not receive appropriately different treatment across the full need distribution, and that this is likely to show a much larger degree of vertical inequity than when the focus is on the consequences of vertical inequity across socioeconomic groups. Thirdly, we demonstrate that by including the need dimension alongside the socioeconomic dimension in the analysis of inequity in health care delivery we are capable of measuring both vertical and horizontal inequity aspects and the consequences that each of them has on the population groups identified by the other, i.e. across need and socioeconomic groups, respectively. This condition highlighted by Gravelle *et al*., 2006 when considering the challenges in the quantification and distinction between horizontal and vertical inequity in health care delivery, was not appropriately met by any of the methodologies used to date in the literature. The fourth original contribution is in terms of the empirical findings with respect to inequity in health service delivery, once we account for vertical inequity. We found that including vertical inequity estimates may lead us to draw different conclusions about the nature and extent of inequity in health service use. Given the large and international body of research that has grown up around the issue of inequities in health care delivery and that currently ignore vertical inequity considerations, this finding is of considerable relevance. Conclusions about the existence of inequity in the provision of health care are therefore extensively being made on the basis of incomplete information.

CHAPTER 2

Inequalities in health in England

2.1. Introduction

Reducing inequalities in health is a top priority in many health care systems, including the NHS in Great Britain. As highlighted in the introduction chapter, evidence suggests that there are persistent inequalities in health in England (see e.g., the Black Report, 1980; the Acheson Report, 1998; the Marmot Review, 2010). Empirical work has largely focused on the measurement of the degree of inequalities in health. The reason is that inequalities need to be a measurable construct in order to provide information on trends and facilitate the debate about whether, for instance, a health care reform has had any impact on health inequalities in a population (Sutton, 2002).

There is much debate about the appropriate measure of health inequalities. The most common approach involves measuring inequalities in health with respect to a *socioeconomic* dimension in order to investigate the gap in health status between those at the top and bottom ends of the socioeconomic scale. Alternatively, the measurement of health inequality can focus on *total* inequalities in health, i.e. including inequality not specifically linked to socioeconomic factors.

In this chapter we aim to explore both income-related inequality in health and total inequality in health in England using the concentration index and the Gini index approach, respectively. In order to explore trends over time and area variation, we use information from nine years of data (1998-2006) and compute the indices separately for the nine Government Office Regions (GOR) in England. In addition, we exploit one useful feature of these measures of inequality, i.e. the possibility of decomposing the inequality index by its explanatory factors. This approach allows us to identify the factors that play a larger role in explaining the observed inequalities in health.

2.2. Methods to measuring and explaining health inequalities

2.2.1. Measuring inequalities in health

Economists have made substantial contributions to the empirical literature on the measurement of health inequalities. Wagstaff *et al.*, 1991a compared a number of measures of health inequality (i.e. the range, the Gini coefficient, the index of dissimilarity, the slope index of inequality, and the concentration index). He suggested the concentration index (CI) to be the most appropriate index to measure the socioeconomic-related inequalities in health. CIs are bivariate measures of inequality, measuring inequality in one variable (in our case health status) related to the ranking of another variable (in our case income). The CI is measured as a function of the share of total health status accounted for by individuals in different parts of the income distribution. According to Wagstaff *et al.*, 1991a, the main advantages of the CI are that they capture the socioeconomic dimension of health inequality, they use information from the full distribution, rather than just the extremes, and they have a graphical representation. In addition, further extensions to the CI allow for the consideration of different levels of inequality aversion and the mean level of health to feature in the index (Wagstaff, 2002). Further, the index can be decomposed in order to explore the factors that contribute to the observed inequality (Wagstaff *et al.*, 2003).

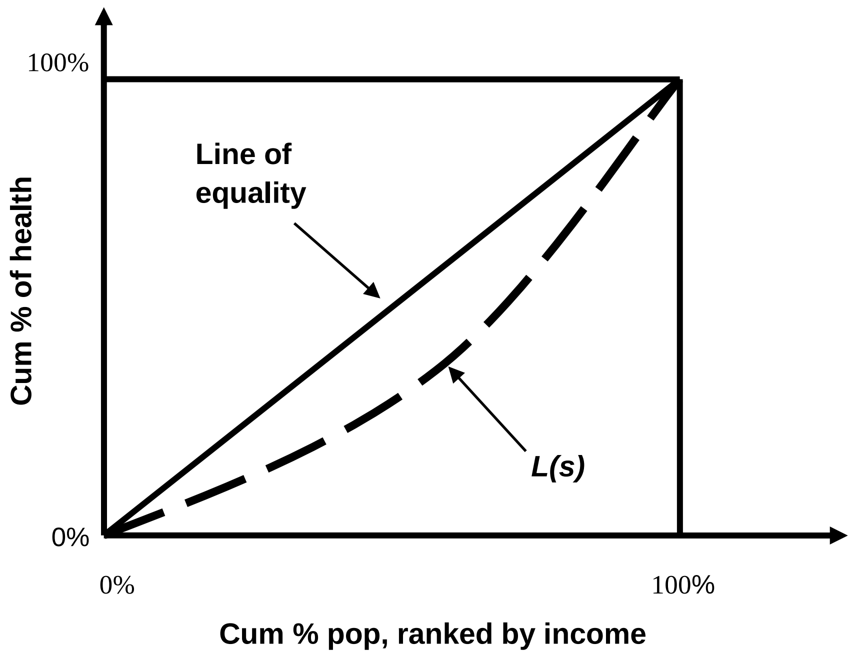
CIs are derived from their corresponding concentration curve (CC) (see Figure 2.1). With a continuous measure of health h_i the concentration curve $L(s)$ plots the cumulative proportion of the population ranked by income against the cumulative proportion of total health[3].

Following Wagstaff, 2002, the CI for income-related inequality in health can be written as follows:

[3] The sort order to generate ranking variables when there were ties in the ordering variable was created according to the sort order of the data using stata command - glcurve. The effects on results are likely to be negligible with unit-record data, and therefore the variables used in this thesis to form the ranking indicators are created to minimize potential ties in their values and provide a finer ranking than that obtained from broad categorical measures.

$$CI = 1 - \frac{2}{n\mu}\sum_{i=1}^{n} h_i (1 - R_i) \qquad (2.1)$$

Figure 2.1. Concentration curve of health with respect to income rank



Where, n is the sample size; h_i is the health variable; μ is the average of the health variable and $R_i = \frac{i}{n}$ is the fractional rank in the income distribution of the ith person, with i =1 for the poorest and $i = n$ for the richest. The concentration index is simply one minus the sum of these weighted health shares ($\frac{h_i}{n\mu}$). The weight attached to each individual's health share is $2(1 - R_i)$, and therefore, the poorest person gets their health share weighted by a number close to two, and then the weights decline in a stepwise fashion, reaching a number close to 0 for the richest person. This weighting may be considered arbitrary. Wagstaff, 2002 proposed an extension to this index that can embody different weighting schemes reflecting different levels of inequality aversion. Since there is no evidence to suggest a preferred value for the aversion to inequality index we use the standard weighting scheme most commonly used in the literature to allow for comparisons with previous studies.

Alternatively, an equivalent estimate can be obtained from a ‘convenient regression’ of a transformation of the health variable of interest on the fractional rank of the income variable (Kakwani *et al.*, 1997). The estimated β coefficient from the following equation provides an estimate of the CI equivalent to that obtained from Equation (2.1),

$$2\sigma_r^2\left(\frac{h_i}{\mu}\right)=\alpha+\beta\ r_i+\varepsilon_i \qquad (2.2)$$

The CI lies between -1 and +1, with a positive (negative) value indicating pro-rich (pro-poor) income-related health inequalities. Standard errors around the CI are derived to assess the statistical significance of the index using the delta method (Rao, 1965). This method can be adapted to account for sampling variability of the mean and to correct for sample weights and data cluster design.

The CI of a bounded variable has been found to depend upon the mean of the variable and hence comparisons of populations with different mean health levels can be problematic (Wagstaff, 2005). We apply the correction proposed by Erreygers, 2009 to account for the bounded nature of our health variable (between zero and one). The formula for the corrected concentration index (CCI) is:

$$CCI=\frac{4*\mu}{a-b}*CI \qquad (2.3)$$

where μ is mean health status and *a* and *b* are the maximum and minimum levels of health (in our case zero and one).

This measure of health inequality picks up the socioeconomic dimension of the inequalities in health. Some authors advocate for the measurement of inequalities in health that also consider other sources of inequalities and suggest focusing on the analysis of total health inequalities (Gakidou *et al.*, 2000). This is accomplished by measuring inequality using the Gini coefficient of health (i.e. the CI of health against the health rank). In the case of the

Gini index, h_i, μ and R_i in Equation (2.1) pertain to the same variable. This measure is analogous to the index developed in the literature on income inequality based on the well-known Gini index of income and derived from the Lorenz curve. In Figure 2.1, if we substitute in the x-axis the cumulative proportion of the population ranked by income by the cumulative proportion of the population ranked by health, the resultant curve is the health Lorenz curve. Since this runs from the sickest to the healthiest individual, the proportion of health accounted for by the least healthy 10% is necessarily less than the proportion of health accounted for by the poorest 10% (unless health and income are perfectly correlated). This implies that the health Lorenz curve must lie below the concentration curve; and therefore the health Gini index is necessarily larger than the CI of health. Only in the case that health and income were perfectly correlated, both indices would coincide. The formula for the health Gini index can be written analogously to the CI as:

$$G = 1 - \frac{2}{n\mu}\sum_{i=1}^{n} h_i (1 - R_i^N) \qquad (2.4)$$

Where R_i^N is the fractional rank in the health distribution. The Gini index lies between 0 and +1, with larger values indicating a larger extent of total health inequalities. We apply the same correction proposed by Erreygers, 2009 to account for the mean dependency problem and compute corrected Gini indices (CGini).

2.2.2. Decomposing inequalities in health by factors

One of the useful features of CIs and Gini indices is that they can be decomposed using regression analysis techniques. This means that it is possible to measure the contribution of different factors (covariates in the regression model) to health inequality (Wagstaff *et al.*, 2003). We start by focusing on the decomposition of the CI. Based on an additive linear regression model of health such as:

$$h_i = \alpha + \sum_k \beta_k x_{ki} + \varepsilon_i \qquad (2.5)$$

where h_i is health status, x_k are a set of demographic factors, socioeconomic variables, and lifestyle indicators, and ε_i is an error term. The CI of health can be written as:

$$CI = \sum_k \left(\frac{\beta_k \overline{x}_k}{\mu}\right) CI_k + \frac{GC_\varepsilon}{\mu} \qquad (2.6)$$

where $\overline{x_k}$ is the mean of x_k, CI_k is the concentration index of x_k (defined analogously to CI) and GC_ε is the generalized concentration index (CI times the mean) for the error term. Therefore, the CI of *h* with respect to income is equal to the weighted sum of the CIs of the explanatory variables and the generalised concentration index of the error term, where the weights are given by the elasticity of *h* with respect to the explanatory variables. Note that the error term of Equation (2.5) differs from that of Equation (2.2) and that the fractional rank is not considered as one of the variables in the set of X variables in Equation (2.5), but rather the income value indicator is included. This could potentially affect the concentration index of the error term used in the decomposition if the wrong functional form for income is used. We applied logarithmic transformation to the income values in every model.

The decomposition of the CI still holds when using the CCI (Erreygers, 2009). The corrected concentration index is defined as:

$$CCI = 4 * \left[\sum_k \left(\beta_k \bar{x}_k CI_k \right) + GC_\varepsilon \right] \qquad (2.7)$$

Using this approach we calculate the contribution of each explanatory variable to income-related health inequality. It is also possible to further disentangle the contribution of these factors into separate components: the impact of the variable on health measured by the coefficient β_k; its unequal distribution across income groups measured by the income concentration index CI_k; and its mean $\bar{x}_k$. The overall contribution to income-related health inequality is the product of the three components, multiplied by four.

Equation (2.6) can also be used to decompose total inequality as measured by the Gini index in exactly the same way. This can be computed directly, by replacing income rank by health rank (van Doorslaer & Jones, 2003).

2.3. Exploring health inequality using the Health Survey for England

2.3.1. Data

The analysis is based on data from nine rounds (1998-2006) of the *Health Survey for England* (HSE) (National Centre for Social Research & University College London). The HSE is a cross-sectional representative national survey which draws a different sample every year of individuals living in England. Respondents are interviewed on a range of topics including their age, socioeconomic status, health status, and lifestyle. The reasons for using this survey are the detailed information on health indicators, in addition to household income and other socioeconomic variables for a large sample and which is available for a considerably large number of years[4]. We include data from 1998 and for individuals over the age of 16 years, as data from younger individuals or earlier survey years do not provide information for some variables of interest. The total sample size in the pooled sample is 98,047 individuals. We divide the sample into three periods of three years each, 1998-2000, 2001-2003 and 2004-2006, in order to explore the trend over time but reduce the impact of random annual fluctuations.

The survey design involved the selection of a random sample of Primary Sampling Units (PSUs) and the selection of a random sample of addresses within each PSU. The PSUs are groups of addresses with postcodes differing only in the last two characters. The size of postcode sectors is of the order of 2,000 households (around 5,000 individuals) and there are around 12,000 of them in the UK. The 2006 HSE includes a boost sample of children aged 2-15 year-old which is not included in the analysis. From 2003, the HSE also provides individual weights to account for non-response.

[4] In particular, the use of the HSE allows us to develop a comprehensive health index based on EQ-5D scores (see details in section 2.3.2). This continuous measure facilitates the analysis of total inequalities in health in addition to the analysis of socioeconomic-related inequalities in health.

2.3.2. Measurement of health status

Our measure of health status is based on the EQ-5D (The Euroqol Group, 1990), which is included in the HSE in 1996 and 2003–2006. The EQ-5D is a generic measure of health status. It is applicable to a wide range of health conditions and treatments, and provides a descriptive profile that is reducible to a single index value for health status. The EQ-5D descriptive system consists of five dimensions – mobility, self-care, usual activities, pain/discomfort and anxiety/depression. Each dimension is scored at one of three levels, depending on whether the respondent has no problems (score=1), some problems (=2) or serious problems (=3) with each dimension. This descriptive system defines 243 EQ-5D health states, plus 'unconscious' and 'dead' giving 245 states in total. Each EQ-5D health state can be converted to a single summary index by applying a formula that attaches weights to each of the levels in each dimension. A number of formulae, or value sets, are available for different countries, based on the valuation of EQ-5D health states from general population samples. The HSE uses weights obtained from the UK population by the Measurement and Valuation of Health Group (The MVH Group, 1995; Dolan, 1997). After applying these weights, an EQ-5D index score of one represents full health, a score of zero is equivalent to death, and negative scores represent health states worse than death.

Our analysis is based on the 1998–2006 rounds of the HSE and in these years EQ-5D data are collected in the HSE in 2003–2006 only. In order to increase our sample size and the number of years covered by our analysis we use predicted rather than actual EQ-5D scores: we use the large set of health indicators collected every year in the HSE to predict EQ-5D index values in 1998–2002. We use ordinary least squares (OLS) to regress EQ-5D scores for 2003–2006 against age, gender and a detailed set of health indicators available in each year of data, and then predict EQ-5D scores for 1998–2006 based on the estimated coefficients. We assume that the coefficients on the predictors are not significantly different to those in the years in our sample with missing EQ-5D data.

The predictors are: gender; a cubic function of individual age; interactions between age and gender; self-assessed health based on responses to the question: 'How is your health in general? Would you say it was… very good, good, fair, bad or very bad?'; whether or not the individual has any of 14 longstanding illnesses by broad disease category; whether or not these longstanding illnesses limit the activity of the respondent in any way; the number of days the respondent had to cut down on their usual activities in the previous two weeks because of illness or injury; and 12-item General Health Questionnaire (GHQ-12) score. The GHQ-12 is a brief self-report measure that has been shown to be a good predictor of psychiatric disorders in non-clinical settings (Goldberg & Williams, 1988). Responses are coded on an unweighted four-point Likert scale (1, 2, 3, 4) where higher scores indicate greater psychological distress or difficulty. An overall score from 0–12 is calculated based on the number of questions to which respondents gave an answer of three or four. We include year dummies to control for potential year effects on the estimation of EQ-5D. Values from the out-of-sample prediction do not include year effects as those cannot be estimated. This is similar to assume that the out-of-sample years were in the omitted category of the year categorical indicator, which was the earliest year with EQ-5D information available, i.e. 2003.

We reduce the model to include only statistically significant variables at a 5% significance level and test for multicollinearity among the variables included in the model using variance inflation factors (VIFs). VIFs for individual covariates greater than ten and a mean VIF across all covariates substantially greater than one are generally seen as evidence of multicollinearity problems (Chatterjee & Hadi, 2006). In order to test the internal validity of the predicted values we check whether using predicted EQ-5D values rather than actual values has an impact on our results in the sample of respondents where actual values were available. We find the results to be very similar using both approaches (see results for the period 2004-2006 using actual EQ-5D values in Appendix 2.1). We also test whether or not the coefficients on the health indicators using data only from 2003 were the same as those using only data from 2006. This is a crude test to assess whether or not the coefficients in the early years of our time series are different to those in later years. We find non-significant differences in the coefficients between these two years of data (p value = 0.5596).

Note that we use predicted EQ-5D scores throughout, even for individuals who report their actual EQ-5D health state in the survey. This provides a measure of health status that is based on the average effect of age, gender and self-reported health on EQ-5D score across individuals from different socioeconomic groups. Compared with using actual EQ-5D scores this approach is likely to remove some of the reporting bias that might occur if, for instance, poor individuals report worse EQ-5D index values for the same health state than rich individuals. An alternative approach would be to regress EQ-5D scores against age, gender, health indicators and socioeconomic status and then predict EQ-5D scores fixing the socioeconomic variables at the same value for every respondent (e.g., at the sample mean). While this may remove socioeconomic reporting bias it would also remove part of the socioeconomic variations in health which we aim to measure in our inequality analysis. A number of studies have used predicted health measures constructed using similar methods to those employed here (i.e., regressing a health measure against age, gender and a series of health indicators; see, e.g., van Doorslaer & Jones, 2003; van Doorslaer & Koolman, 2004; and Sutton, 2002).

Using the EQ-5D, negative values represent health states worse than death. In order to compute concentration indices, in our analysis negative values are set to equal zero for the computation of the inequality indices (this applies to 31 observations; 0.03% of the sample)

2.3.3. Measurement of income

Income is included as the log transformation of a continuous variable based on the prediction of an interval regression model of annual household income reported in 31 income bands, against a set of individual and household characteristics. The predicted values are fixed to fall within the range of the original income band, and are equivalised using the weights provided in the HSE to account for household composition. Observations with missing income values are not included in the analysis (around 19% of the sample). We explore whether or not including observations with missing income values had an impact on our results. We impute income based on out of sample predictions from the interval regression model of income bands. The results were found to be consistent when we include these observations and are presented in Appendix 2.2.

2.3.4. Other covariates

In the decomposition of health inequality by factors we also include: social class of head of household (measured in seven categories); highest education qualification (seven categories); ethnicity (eight categories); housing tenure (five categories); marital status (five categories); and lifestyle factors (smoking and obesity).

We include regional indicators in our analysis defined by Government Office Regions (GORs), of which there were nine in England during the period of our analysis. We also control for area characteristics measured at the Primary Sampling Unit (PSU) level in which the survey respondent lives. Previous studies have shown that area characteristics measured at this or similar levels are correlated with individual health (see, e.g., Reijneveld *et al.*, 2000). PSUs are the only small area available in each year of our data. Similar exploitation of PSU level data has been used to good effect in previous studies (see, e.g., Mohan *et al.*, 2005). We include five variables: the proportion of the sample in the PSU with equivalised household income in the bottom quintile of the national distribution; the proportion with no education qualifications; the proportion in the White ethnic group; the proportion reporting very bad health; and the proportion reporting having to cut down on normal activities due to illness or injury in the last two weeks.

2.3.5. Regression analysis and sampling issues

The decomposition results are based on an OLS regression model of our derived measure of health against demographic, socioeconomic, lifestyle and area characteristics, controlling for year of data and missing values. To maximise the sample missing values for binary and categorical variables were assigned to the omitted category. To allow for the possibility that items were not missing at random we included dummy variables for all imputed items to indicate item non response. We apply survey weights reported in the HSE from 2003 to each observation (observation from previous years were assumed to have a weight equal to one) and we control for PSU-level clustering in every regression using unique PSU/year identifiers.

Standard errors of the estimates of the contribution of the covariates to health inequality in the decomposition analysis were computed using bootstrapping techniques (van Doorslaer *et al.*, 2004). To allow for differences in sample probabilities, we expanded our sample size by multiplying the sampling weights by 10 and then replace each observation in the dataset with *n* copies of the observation, where *n* is equal to sampling weight*10 rounded to the nearest integer. From this inflated sample we draw a random subsample of the size of the original sample with replacement, and estimate the contribution of each of the explanatory factors included in the regression. We run this procedure 500 times and compute the standard deviations for each of the contributions. This allows us to assess the statistical significance of the contributions of each explanatory variable to income-related health inequality and overall inequalities in health.

P values below the 5% level (z scores higher than 1.9) are regarded as statistically significant. Values between 5% and 10% (z scores between 1.6 and 1.9) are regarded as weakly significant. All analyses were undertaken using Stata version 11.

2.4. Empirical results

The results of the OLS model of EQ-5D score against age, gender and the health indicators are in Table 2.1. We find that indicators of ill health and the presence of some longstanding illnesses are negatively correlated with EQ-5D score. Other than in the case of the six age variables there is no evidence of multicollinearity problems: the largest VIF was 2.03 and the mean of all the VIFs is 1.14. The outcomes of the interval regression model of income bands against individuals and household characteristics are reported in Table 2.2. All variables are significant and have the expected sign, with lower socioeconomic status being negatively correlated with income.

Table 2.3 summarises the mean health, mean income, CCIs and CGini indices of inequality in health by area and by period. Areas are ranked according to their pooled level of income-related inequality as given by the *'All years'* CCI. The CCIs are all positive, showing that health is concentrated among the rich. All the CCIs are significantly different from zero. Nationally, the CCI increased by around 10% in 2001-2003 compared with 1998-2000, but in 2004-2006 it decreased to a level just slightly higher than in the first period. There are regional variations in the level of income-related inequality: it is lowest in London, the East and the South of England – which are areas with relatively high mean health and income – and highest in the North and West – areas with relatively low mean health and income. Most areas follow the national trend in changes in inequality over the three time periods, but in some areas the pattern is different. For example, in the area with the highest income-related inequality (the North East), inequality increased over the whole period, while in the areas with lower income-related inequality, e.g., London, the South East and the South West, the inequality level in the latest period is lower than in the first period. Figure 2.2 shows these results graphically for ease of comparison.

Table 2.1. Reduced OLS model of EQ-5D on age, gender and health indicators

	Mean	SD	Coeff	z		Mean	SD	Coeff	z score
Age and gender					***Longstanding***				
Age	0.477	0.187	-0.012	-0.11	Infectious disease	0.002	0.045	-0.059	-2.01
Age-squared	0.263	0.191	0.018	0.07	Mental disorders	0.031	0.174	-0.063	-9.13
Age-cubed	0.160	0.164	-0.134	-0.77	Nervous system	0.039	0.192	-0.045	-7.20
Female	0.534	0.499	0.058	2.76	Digestive system	0.049	0.216	-0.010	-2.01
Female*age	0.258	0.278	-0.340	-2.18	Musculo-skeletal	0.194	0.396	-0.113	-36.57
Female*age-squared	0.144	0.197	0.578	1.66	***GHQ-12 score***				
Female*age-cubed	0.089	0.150	-0.352	-1.48	0	0.575	0.494	Base category	
Self-assessed general health					1	0.122	0.328	-0.030	-12.95
Very good	0.325	0.469	Base category		2	0.067	0.250	-0.053	-15.15
Good	0.417	0.493	-0.017	-13.03	3	0.042	0.200	-0.078	-16.60
Fair	0.188	0.391	-0.076	-27.54	4	0.030	0.170	-0.091	-0.091
Bad	0.053	0.224	-0.269	-34.72	5	0.023	0.151	-0.113	-15.95
Very bad	0.016	0.127	-0.405	-28.99	6	0.018	0.131	-0.124	-14.00
Acute ill health (days cut down)					7	0.014	0.119	-0.145	-14.76
0 days	0.833	0.373	Base category		8	0.012	0.108	-0.150	-13.95
1-3 days	0.047	0.212	-0.013	-3.11	9	0.010	0.098	-0.172	-13.17
4-6 days	0.026	0.159	-0.031	-4.76	10	0.009	0.096	-0.205	-15.03
7-13 days	0.028	0.166	-0.047	-7.16	11	0.008	0.090	-0.236	-14.64
14 days	0.065	0.247	-0.088	-15.79	12	0.009	0.094	-0.266	-17.39
Limiting longstanding					N		39,662		
Yes	0.260	0.438	-0.069	-22.59	R^2		0.576		

Note: Coeff = Coefficient; SD = Standard Deviation

The model also controls for year of data and missing values. Sample weights are used and we adjust for clustering at the Primary Sample Unit level.

Table 2.2. Interval regression model of household income on individual and household characteristics

	Mean	SD	Coeff	z
Age and sex				
Female	0.532	0.499	-9271.9	-3.14
Age/100	0.473	0.183	-31762.4	-1.73
Age-squared/10000	0.257	0.185	45845.4	1.24
Age-cubed/1000000	0.155	0.158	-31057.5	-1.33
Female*age/100	0.253	0.273	55377.6	2.95
Female*age-squared/10000	0.139	0.190	-109289.9	-2.90
Female*age-cubed/1000000	0.084	0.144	69062.0	2.88
Social class of head of household				
Professional	0.072	0.258	Base category	
Managerial/technical	0.330	0.470	-4458.6	-6.29
Skilled non-manual	0.145	0.352	-13507.2	-18.66
Skilled manual	0.250	0.433	-14337.7	-20.33
Semi-skilled manual	0.135	0.342	-14810.2	-20.46
Unskilled manual	0.045	0.208	-15455.6	-21.20
Other	0.023	0.150	-13996.5	-14.55
Economic activity				
In paid employment	0.565	0.496	Base category	
Going to school/college full time	0.049	0.217	-768.4	-1.15
Permanent long term sickness	0.041	0.198	-8222.0	-25.81
Retired from paid work	0.214	0.410	-7644.3	-20.74
Looking after the home	0.100	0.300	-4026.7	-12.03
Waiting to take up paid job	0.003	0.052	-3782.5	-1.71
Looking for paid job	0.019	0.137	-9357.0	-13.98
Temporary sickness or injury	0.004	0.062	-10030.4	-9.22
Doing something else	0.002	0.050	-6859.5	-5.60
Education				
Degree	0.167	0.373	Base category	
Higher education less than degree	0.113	0.316	-9281.0	-21.51
A level or equivalent	0.122	0.327	-7707.2	-17.21
GCSE or equivalent	0.234	0.424	-9967.8	-24.60
CSE or equivalent	0.053	0.223	-11141.6	-21.36
Other qualification	0.036	0.186	-10735.9	-19.03
No qualification	0.273	0.446	-10671.6	-25.03
Ethnic group				
White	0.929	0.257	Base category	
Black Caribbean	0.011	0.105	-5198.5	-6.36
Black African	0.008	0.090	-8385.7	-5.50
Indian	0.016	0.125	-4095.5	-2.80
Pakistani	0.009	0.094	-9076.8	-5.95
Bangladeshi	0.003	0.059	-10160.5	-4.34
Chinese	0.002	0.047	-5068.0	-1.92
Other	0.016	0.124	-3571.3	-3.42
Number of cars in household				
No car	0.200	0.400	Base category	
One	0.429	0.495	1617.0	5.49
Two	0.298	0.457	11388.3	27.02
Three or more	0.073	0.260	23953.8	26.65
Bedrooms per person	1.289	0.677	1124.9	5.53
Marital status				
Married	0.558	0.497		
Single	0.252	0.434	-4291.2	-11.44
Separated	0.022	0.147	-5551.1	-10.06
Divorced	0.073	0.260	-4598.5	-12.03
Widowed	0.084	0.277	-3066.5	-7.90
Tenure				
Own	0.276	0.447	Base category	
Mortgage	0.461	0.498	4357.5	10.81
Part mortgage	0.005	0.071	-3735.6	-3.72
Rent	0.249	0.432	-2795.0	-7.61
Free rent	0.009	0.095	-5154.6	-5.58
σ			19842.8	249.75
N			79380	
R^2			0.075	

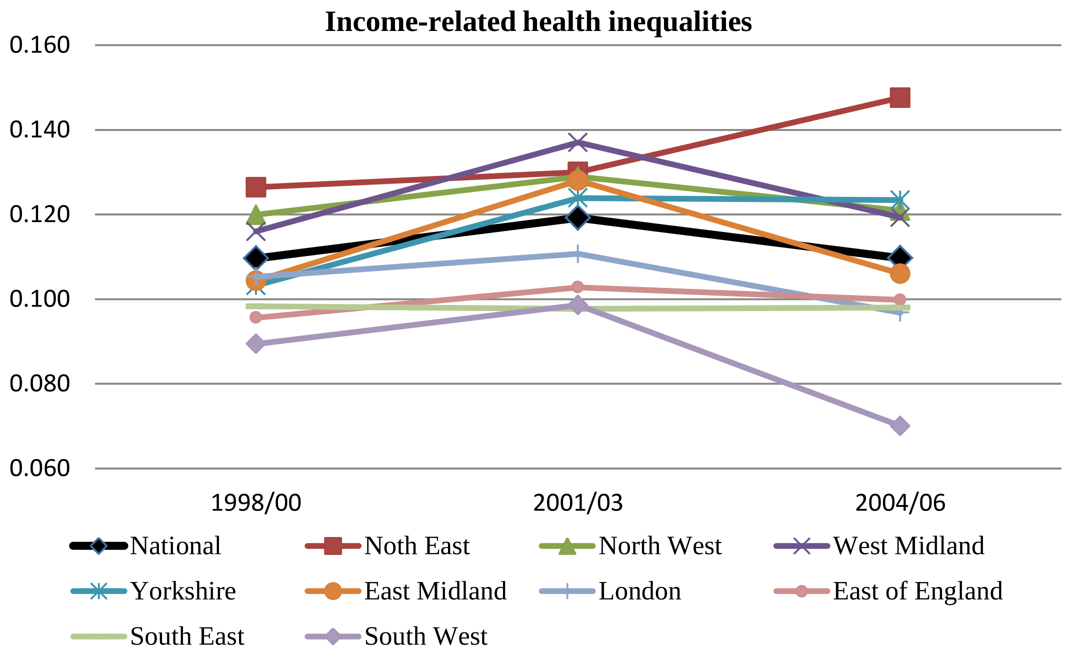
Model control for year of data, GOR of residence and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level.

Table 2.3. Health, income, and health inequality by year and by area

	Health	Income	CCI	CGini	N
National					
1998-2000	0.846	£20,906	0.1096	0.3467	26,303
2001-2003	0.852	£26,039	0.1192	0.3410	30,495
2004-2006	0.860	£29,171	0.1097	0.3258	22,547
All years	0.853	£25,394	0.1140	0.3385	79,345
North East					
1998-2000	0.808	£15,547	0.1264	0.4311	1,644
2001-2003	0.820	£21,379	0.1300	0.4073	2,060
2004-2006	0.822	£23,381	0.1476	0.4264	1,355
All years	0.817	£20,073	0.1332	0.4196	5,059
North West					
1998-2000	0.833	£18,897	0.1199	0.3784	3,551
2001-2003	0.835	£22,835	0.1289	0.3759	4,161
2004-2006	0.847	£27,254	0.1209	0.3512	3,106
All years	0.838	£22,971	0.1249	0.3697	10,818
West Midlands					
1998-2000	0.838	£17,939	0.1160	0.3607	2,938
2001-2003	0.842	£23,334	0.1370	0.3659	3,238
2004-2006	0.848	£25,806	0.1193	0.3465	2,452
All years	0.843	£22,360	0.1242	0.3585	8,628
Yorkshire					
1998-2000	0.838	£18,764	0.1032	0.3708	2,762
2001-2003	0.843	£22,249	0.1239	0.3667	2,964
2004-2006	0.849	£26,825	0.1234	0.3529	2,408
All years	0.843	£22,526	0.1177	0.3642	8,134
East Midlands					
1998-2000	0.843	£18,297	0.1043	0.3553	2,409
2001-2003	0.842	£23,905	0.1280	0.3532	2,899
2004-2006	0.855	£26,718	0.1060	0.3295	2,051
All years	0.846	£22,978	0.1139	0.3474	7,362
London					
1998-2000	0.850	£25,029	0.1053	0.3398	2,928
2001-2003	0.865	£30,917	0.1107	0.3158	3,494
2004-2006	0.880	£32,881	0.0968	0.2934	2,354
All years	0.866	£29,832	0.1071	0.3169	8,773
East of England					
1998-2000	0.864	£23,214	0.0956	0.3081	3,182
2001-2003	0.869	£28,546	0.1028	0.3012	3,656
2004-2006	0.868	£30,831	0.0998	0.3017	2,743
All years	0.867	£27,587	0.0991	0.3035	9,581
South East					
1998-2000	0.861	£25,440	0.0983	0.3033	4,035
2001-2003	0.867	£31,802	0.0977	0.3003	4,919
2004-2006	0.875	£33,975	0.0980	0.2922	3,840
All years	0.868	£30,596	0.0988	0.2991	12,794
South West					
1998-2000	0.858	£20,405	0.0894	0.3108	2,758
2001-2003	0.862	£23,797	0.0986	0.3189	3,094
2004-2006	0.867	£28,284	0.0700	0.2980	2,242
All years	0.862	£24,068	0.0872	0.3102	8,094

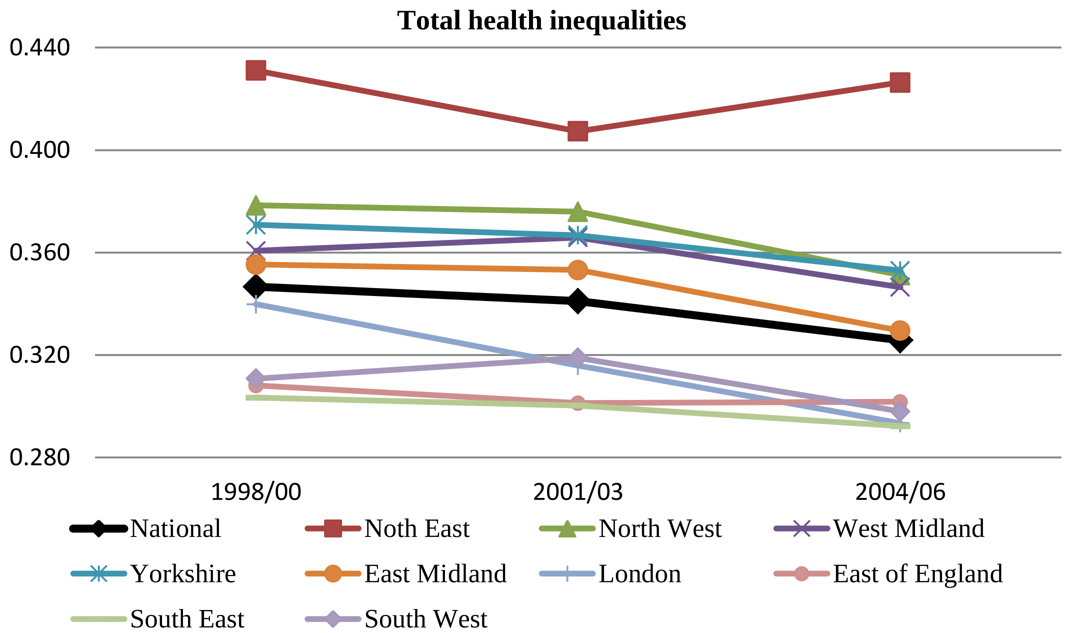
Note: CCI = corrected concentration index; CGini = corrected Gini index. All indices are statistically significantly different from zero

Figure 2.2. Income-related inequalities in health over time and across areas



The level of *total* inequality in health as measured by the CGini index of health appears to be decreasing across the full period under analysis, both nationally and in most of the geographical areas separately. The indices are nevertheless all significantly different from zero, indicating that there is inequality in health in every period and area of England, but the magnitudes are slightly decreasing. As expected, the indices of total inequality are larger than the indices of income-related inequalities in health. There is again a North-South gradient in the values of the health CGini indices, where the North experiences relatively high levels of total health inequality, while the indices in the South and East are relatively smaller. The ranking of areas according to the CGini index of inequality would slightly vary as compared to that based on the CCIs of income-related inequalities in health. The South East does now show the lowest degree of inequality, rather than the South West; and Yorkshire has an estimated larger total inequality level as compared with the West Midlands (the opposite results was found with respect to the CCI). These findings are summarised in Figure 2.3.

Figure 2.3. Total inequalities in health over time and across areas



Moving to the results of the decomposition by factor of the inequality levels, Table 2.4 presents the results of the variables with the largest contribution in the decomposition for the pooled national model that combines information from every year of data and every area of England. Full results are presented in Appendix 2.3. We report the average value of each explanatory factor ("Mean"), the effect of each variable on health ("Coeff"), and the concentration ("CI") of the variable with respect to the ranking variable (i.e. with respect to income in the decomposition of the CI and with respect to health in the decomposition of the CGini index). The contributions are presented as an overall contribution ("Cont") and as a percentage to the health inequality index ("%").

In terms of the factors explaining income-related inequality in health, as one would expect, income makes the largest contribution (35%), followed by age and gender[5] (24%). The next largest contributor is housing tenure (11%), followed by education (8%) and the area characteristics (5%). Lifestyle factors, measured by smoking and obesity, make the next largest contribution, followed by the social class of the head of household, marital status,

[5] Note that the contribution of age and gender to both income-related and overall inequalities in health might be considered unavoidable and therefore some analysts would prefer to standardise by age and gender before computing the inequality index. However the fact that, for instance, elderly or females might tend to have worse health and lower incomes may also be viewed as unfair. The decomposition approach allows for the contribution of age and gender to inequalities in health to be accounted for but also measured separately.

area, and ethnic group. Overall, using the decomposition based on our regression model, the percentage of the explained income-related inequality in health is over 94%.

The explained percentage of the CGini index of total health inequality is considerably lower, just below 30%. As noted by van Doorslaer and Jones, 2003, the reason is that income is one of the explanatory variables in the model, and thus, our regression model explains more of the income-related variation in health than of the total variation in health. In terms of the factors playing a larger role in explaining total inequalities, age and gender are the largest contributors (20% overall; 65% of the explained total inequality). Income follows as the next contributor factor (3% overall; 10% of the explained total inequality). Education makes the next largest contribution, followed by the area characteristics, lifestyle factors, housing tenure, area, social class, and marital status.

2.5. Discussion and implications of findings

In this chapter we have measured income-related health inequality and total health inequalities using a representative dataset for England from 1998 to 2006, and across nine regions. We found that health is significantly concentrated among the rich in every period and area. The indices of total inequalities in health were found to be considerably larger than the income-related inequalities in health, on the order of more than three times the corresponding CCIs. These results are in line with previous literature that has found the income-related inequalities in health to be approximately 25% of the total inequalities in health using different sets of data such as malnutrition amongst Vietnamese children and health utility amongst Canadian adults (Wagstaff & van Doorslaer, 2004).

As Wagtaff and van Doorslaer, 2000 pointed out, in the measurement of inequalities in health examining a system in isolation is less helpful for policy purposes than comparative studies. We computed inequality indices across a period of time and for nine regions of England in order to provide evidence of time trends and area variation. Income-related inequality increased slightly over the period.

Table 2.4. OLS model of health status, and decomposition of the concentration index and Gini coefficient (selected results)

	Regression model			Decomposition CCI					Decomposition CGini				
	Mean	Coeff	z	CI	Cont	z*	Percent	%	CI	Cont	z*	Percent	%
Age and gender													
Age	0.473	-0.307	-3.54	-0.039	0.0227	3.04	19.93		-0.103	0.05950	3.61	17.58	
Female	0.532	0.008	0.54	-0.039	-0.0007	-0.51	-0.58		-0.051	-0.00083	-0.55	-0.25	
Age-squared	0.257	0.022	0.11	-0.087	-0.0020	-0.10	-1.74		-0.191	-0.00426	-0.11	-1.26	
Age-cubed	0.155	-0.036	-0.27	-0.134	0.0031	0.25	2.72		-0.263	0.00584	0.27	1.73	
Female*age	0.253	-0.078	-0.73	-0.078	0.0064	0.67	5.61		-0.160	0.01254	0.74	3.71	
Female*age-squared	0.139	0.117	0.49	-0.125	-0.0086	-0.46	-7.56		-0.253	-0.01645	-0.49	-4.86	
Female*age-cubed	0.084	-0.097	-0.59	-0.171	0.0060	0.56	5.27	23.6	-0.327	0.01072	0.59	3.17	19.8
Log equivalised income	9.834	0.023	21.41	0.045	0.0403	22.12	35.34	35.3	0.012	0.01063	17.00	3.14	3.1
Education													
Degree	0.167	Base category											
Higher education less than degree	0.113	-0.001	-0.66	0.192	-0.0001	-0.67	-0.09		0.066	-0.00004	-0.70	-0.01	
A level or equivalent	0.122	-0.006	-3.02	0.151	-0.0004	-3.05	-0.35		0.173	-0.00048	-3.33	-0.14	
GCSE or equivalent	0.234	0.000	-0.22	0.003	0.0000	-0.08	0.00		0.104	-0.00004	-0.22	-0.01	
CSE or equivalent	0.053	-0.005	-1.89	-0.229	0.0003	1.83	0.23		0.003	0.00000	-0.27	0.00	
Other qualification	0.036	-0.003	-0.74	-0.150	0.0001	0.70	0.05		-0.185	0.00007	0.74	0.02	
No qualification	0.273	-0.024	-10.56	-0.331	0.0091	10.52	7.97	7.8	-0.273	0.00701	9.48	2.07	1.9
Tenure													
Own	0.276	Base category											
Mortgage	0.461	-0.007	-4.00	0.260	-0.0032	-3.87	-2.85		0.175	-0.00230	-4.14	-0.68	
Part mortgage	0.005	-0.024	-2.59	-0.213	0.0001	2.22	0.08		-0.011	0.00001	0.26	0.00	
Rent	0.249	-0.040	-18.23	-0.384	0.0151	17.35	13.21		-0.124	0.00490	12.37	1.45	
Free rent	0.009	-0.015	-2.20	-0.155	0.0001	1.78	0.08	10.5	-0.086	0.00005	1.41	0.01	0.8
Lifestyle													
Smoking	0.253	-0.022	-15.31	-0.121	0.0027	13.62	2.33		-0.030	0.00067	5.30	0.20	
Obesity	0.199	-0.031	-20.30	-0.055	0.0014	10.23	1.17	3.5	-0.112	0.00276	12.36	0.82	1.0
Area characteristics													
Mean reporting very bad health	0.016	-0.447	-20.59	-0.116	0.0034	10.12	3.01		-0.094	0.003	10.05	0.81	
Mean reporting cutting down 14day	0.066	-0.218	-23.89	-0.052	0.0030	9.48	2.63		-0.071	0.004	12.82	1.20	
Mean no qualifications	0.287	0.021	4.23	-0.087	-0.0021	-3.88	-1.82		-0.039	-0.001	-4.53	-0.27	
Mean white ethnic group	0.925	0.012	2.30	0.005	0.0002	2.14	0.20		-0.001	0.000	-1.58	-0.01	
Mean low income	0.192	-0.012	-2.28	-0.165	0.0015	2.24	1.33	5.4	-0.059	0.001	2.16	0.17	1.9

Note: Coeff = Coefficient; Cont = Contribution; Percent = Percentage contribution. *Standard errors for contributor factors are derived using bootstrapping techniques. The model also includes social class, ethnicity, marital status, area, year, and missing values. Sample weights are used and we adjust for clustering at the Primary Sample Unit level

These findings have resonance with previous studies that have explored income-related inequality trends for the UK in earlier years and have found modest increases in inequality between 1994 and 1996 (Hernandez-Quevedo *et al.*, 2005); inequalities in health were also found in that study to widen overtime for most European countries. In an early study by Propper and Upward, 1992 income-related health inequalities in the UK were found to increase from 1974 to 1985 and then to fall in 1987; comparing 1974 with 1987 the authors found little worsening of income-related inequalities. Gravelle and Sutton, 2002 measured income-related inequalities in health from 1979 to 1995 using the partial concentration index (Gravelle, 2003) defined as the individual contribution of income to income-related inequalities in health. They found an increase in inequalities in England, Wales and Scotland throughout this period. Interestingly, in the case of Gini indices of inequalities in health, our finding suggests that the level of total health inequality is decreasing over time. This result is consistent with early contributions to the measurement of total inequity by Illsley and Le Grand, 1987 that found the Gini coefficient of age-at-death for England and Wales to fall almost continuously from 1921 to 1983.

In our study, the extent of health inequality (both in terms of income-related and total inequality) was found to vary between regions. A North-South gradient has previously been reported in the literature both in terms of deprivation and health status (Woods *et al.*, 2005). We also found that poorer areas and those with worse health were also those with the highest levels of income-related and total health inequalities. In the case of income-related inequalities, areas with relatively high level of inequality at the initial period were also experiencing the largest increases in inequality over time; while in the areas with relatively low levels, the estimates were found to decrease further during the period. These trends lead to a reported increase in income-related health inequality between areas of England (Department of Health, 2008a).

The conclusions regarding the trend over time in inequalities in health are thus not necessarily consistent when the focus is on total inequality rather than on income-related inequality in health. Our results also suggest that the ranking of areas with respect to the CIs and with respect to the Gini indices would differ. Therefore, although some authors have highlighted the direct relationship between the CI and the Gini coefficient[6], the results of this study suggest that the choice between the Gini index and the concentration index as the measure of inequality in health is not unimportant.

This is a long-standing issue in the literature on health inequalities (Wagstaff, 2001; Bleichrodt & van Doorslaer, 2006). Some authors favour the use of the CI arguing that what it is worrying is not that health inequalities exist, but that they mirror inequalities in socioeconomic status (e.g. Wilkinson, 1986). This is consistent with the view that while it might be accepted that health differences arise from luck or chance, health differences that arise from socioeconomic circumstances might be considered an infringement on social justice. However, other analysts (e.g. Gakidou *et al.*, 2000) have claimed that '*we should be concerned with inequality in health, whether or not it is correlated with inequality in other dimensions of well-being'*, and therefore favour the use of total inequalities measures. As Wagstaff and van Doorslaer, 2000 highlight, advocates of the total inequality in health approach considered the analysis of the socioeconomic dimension as part of the process of *explaining* health inequalities, not part of the process of *measuring* them (e.g. Illsley & Le Grand, 1987). In empirical studies, the choice between the two estimates is often limited by the availability of the data. In most cases, information on health status is limited to categorical variables which prevent from deriving a ranking variable of the population based on their health status that would allow the analysis of total health inequality.

Moving to the results from the decomposition analysis, we found that income-related inequalities in health are mainly explained by the effect that socioeconomic factors such as income and education have on health status, which is exerted by their influence on intermediary factors, such as health-damaging behaviours and poor living conditions. Our findings suggest that in order to reduce income-related inequalities in health, policies that aim at improving the underlying social determinants of health such as the income distribution, housing conditions and education are likely to have the largest impact on income-related health inequality. Income was also found to be the second largest contributor, only surpassed by the contribution of age and gender, to total inequalities in health. However, albeit its statistically significant contribution, the magnitude was found to be relatively small (3% of overall total inequity; 10% of the explained total inequity). As noted above, based on our regression model, a large

[6] The CI is proportional to the Gini index for health, where the factor of proportionality is given by the ratio between the correlation coefficient of health and income rank and the correlation coefficient of health and the health rank (Kakwani, 1980; van Doorslaer & Jones, 2003; Hernandez-Quevedo *et al.*, 2005)

fraction of the Gini index of health remains unexplained. Further work to investigate the underlying factors that explain total inequalities in health is thus needed.

Van Doorslaer and Jones, 2003 decomposed both the CI and the Gini coefficient of self-assessed health and the health utility index using data from 1994-1995 from a Canadian sample. They found very similar results as reported in this study, and highlighted that caution is required in giving a causal interpretation to the results of the regression analysis and thus to the decomposition analysis as based upon those. The results from our analysis tell us about the association between health and factors such as income and lifestyle, but conclusions about a causal relationship of these effects on health cannot be drawn. Reverse causality, correlation with an omitted variable, or measurement error of the covariates that correlate with the dependent variable may be affecting the observed relationship between some of the explanatory variables and health status. More recent work to overcome this issue when the focus is on a particular variable have involved the use of econometric techniques that control for the potential endogeneity of the variable of interest and health status (see e.g. Balia & Jones, 2008; Vallejo-Torres & Morris, 2010a).

In conclusion, although evidence shows that England is now healthier than ever, the gap in health status between those at the top and bottom ends of the income scale remains large and in some areas, particularly in the most deprived regions, it continues to widen. When allowing for other sources of inequalities in health, the measurement of total inequalities indices are significantly larger, but are slightly decreasing overtime. The choice between income-related and total inequalities in health is not uncontroversial, and the results of this study suggest that the main conclusions regarding time trends and regional variation are sensitive to the measure being used. Finally, income and education are the socioeconomic indicators making the largest contribution to explaining income-related inequalities, while income plays also a statistically significant but modest role in explaining total inequalities in health.

Persisting inequalities in health have contributed to the emphasis of ensuring equity in the distribution of health care in many health care systems. In the next chapter we illustrate the methods widely applied for the measurement of inequity in the distribution of health care in the literature and highlight some limitations.

CHAPTER 3

Horizontal inequity in the use of primary care services in England

3.1. Introduction

In the previous chapter we explored and quantified inequalities in health in England. Inequities in the delivery of health care are also a major concern in many health care systems, and some including the UK, distribute health care resources on the basis of explicit equity objectives.

In empirical studies of equity in the delivery of health care most of the attention has been paid to the notion of 'equal treatment for equal need' which has been labelled *horizontal* equity in health care utilisation. According to this principle, patients with equal needs for health care should receive the same treatment, irrespective of other characteristics such as income, race or place of residence. In empirical investigations the focus is commonly on deviations of this principle with respect to the socioeconomic dimension.

In this chapter we aim to illustrate the methods commonly used for the analysis of horizontal inequity in the literature and to highlight the main limitations of focusing solely on horizontal inequity, i.e. it ignores the possibility that the estimated differential treatment received by individuals with different needs is inappropriate, i.e., vertical inequity aspects. In order to do so, we explore horizontal inequity in primary care services using the Health Survey for England.

An additional contribution with respect to the literature on horizontal inequity in primary care services is that, unlike previous studies which focus on GP service use only, we consider GP and practice nurse use, and allow these types of use to be correlated. We compare the factors that determine GPs and practice nurse use and the estimates of horizontal inequity of both types of health contacts. This allows us to draw more robust conclusions about the extent of horizontal inequity in primary care in England.

We begin by summarising previous evidence on horizontal inequity in the use of primary care services in the literature. The rationale for including considerations for practice nurse service use in equity analyses is presented next. Section 3.4 illustrates the methods commonly used for the measurement and explanation of horizontal inequity in the literature. Data and empirical methods for the estimation are then presented. Empirical results are summarised in section 3.6 and the final section concludes and provides the discussion of the main results.

3.2. Previous evidence of horizontal inequity in primary care in the UK

The vast majority of previous studies of horizontal inequity in health care delivery in the UK have shown a consistent pattern which is also found in most of OECD countries (see Goddard & Smith, 2001; Dixon *et al.*, 2007 for a review of inequity studies in the UK; and van Doorslaer *et al.*, 2006 for the latest and largest comparative study of inequity across OECD countries). The evidence in the literature commonly indicate that while secondary care services tend to be disproportionally concentrated among the better off, primary care services are broadly equitable, and any significant inequity that emerges often benefits those with lower incomes.

With regards to previous studies on equity in primary care, the attention has been limited to the use of GP services. According to a review by Goddard and Smith, 2001 over the period 1990-1997, the evidence suggests a pro-poor distribution of GP consultations in the UK, with the exception of GP visits for preventive care (McCormick *et al.*, 1995). Van Doorslaer *et al*., 2000 used the General Household Survey for 1989, and found that GP utilisation is more frequent in low income groups, but after standardising for age, gender and health, there is little or no inequity in the distribution of GP care. Using the European Community Household Panel for 1996, van Doorslaer *et al.*, 2004 studied 12 European countries and concluded that the rich and the poor face very similar probabilities of seeing a GP after controlling for need. In the case of the UK, they found pro-rich horizontal inequity in the probability of visiting a GP, but pro-poor indices in the case of conditional use (among those with at least one visit) and in the case of total GP visits. Using the same survey but exploring data from 2001, van Doorslaer *et al.*, 2006 reported that the probability of seeing a GP is equally distributed across the income distribution in the UK, but lower-income patients, once they see a GP, are more likely to consult more often, finding a pro-poor distribution of total GP visits. Other studies have identified sources of horizontal inequity in GP care in England. Using the Health Survey for England (HSE), Morris *et al.*, 2005 found that, after controlling for a wide range of health indicators, those with lower education attainment were more likely to visit their GP, and non-whites were generally more likely to consult GPs relative to whites. Those looking for paid work and those in full time education, had a lower probability of consulting a GP compared with those in paid employment.

As noted above, previous studies in primary care have focused on GP contacts. Rising demand for and costs of health care have led to an increasing role of practice nurses in primary care in many countries, and notably in the UK.

3.3. The increasing role of practice nurses in primary care

The demand for primary care services is rapidly increasing in most developed countries due to population ageing, medical advances that increase patient's expectations and prolong life expectancy, and reforms that shift care from hospitals to the community (Laurant *et al.,* 2005). As a response to the rising demand and costs, the role of practice nurses in primary care has been expanded and developed, especially in Western Europe. In some countries, notably the UK, nurses have moved to more advanced roles becoming first line care providers and leading the management of patients with stable chronic conditions such as asthma, diabetes and cardiovascular disease (Sibbald *et al.*, 2006).

Practice nurses are registered general nurses who may have a variety of post-registration qualifications and expertise. In the NHS in England they are employed by GPs and they provide a substantial amount of care to patients in the primary care system (Williams & Sibbald, 1999; Chapple *et al.*, 2000; Royal College of General Practitioners, 2004). Between 1997 and 2007 the number of full time equivalent practice nurses in England rose by 44% from 10,082 to 14,554 (Information Centre for Health and Social Care, 2008a). This increase has arisen partly as a result of the delegation of tasks traditionally performed by other members of the primary care team to practice nurses, and partly via the diversification and extension of the range of services provided within primary care (Laurant *et al.,* 2005; Williams & Sibbald, 1999).

For example, the practice nurse role is being increased in the management of patients with long term conditions (Department of Health, 2002). Some GPs have delegated the routine care of patients with asthma to practice nurses, and a number of practice nurses have undertaken specialist training in asthma care allowing practices to offer a wider range of services than was previously available (Williams & Sibbald, 1999).

Previous research has explored how practice nurse care differs from that provided by GPs in terms of costs and health outcomes. Two systematic reviews (Laurant *et al.,* 2005; Horrocks *et al.*, 2002) concluded that appropriate trained nurses can produce high quality care and achieve similar health outcomes for patients to GPs in certain aspects of primary care. In some respects, nurses were found to provide better outcomes; for instance, patients' satisfaction was found to be significantly greater with practice nurses than with GPs. Savings in cost were found to depend on the magnitude of the salary differential between doctors and nurses, and may be offset by the lower productivity of nurses compared with doctors (arising because nurse consultations were longer and generated more tests, referrals and patient recalls). Hollinghurst *et al.*, 2006 compared the cost of nurse practitioners and GPs in primary care, and found that employing a nurse practitioner is likely to cost as much as employing a GP. As this study concluded, this indicates the importance of matching skills and experience with roles and responsibilities.

Despite the importance of exploring the role of GPs and practice nurses in terms of the characteristics of the patients they serve, there has been little research to investigate differences in the use of these two types of services. Consideration of practice nurse use in equity analysis of primary care is important because, as noted above, the roles of practice nurses are to support and extend the role of GPs, and so identifying the factors associated with the use of these services allows us to make more robust claims about the extent of horizontal inequity in primary care services. For example, suppose there is evidence of pro-rich inequity in the use of GP services. Analysis of the factors associated with visits to the practice nurse is informative; to illustrate, consider two possible scenarios:

(1) There is also pro-rich inequity with respect to practice nurse visits. Therefore, the extent of the inequity is greater than originally thought because it also persists with respect to practice nurses.

(2) There is no evidence of pro-rich inequity in the use of practice nurse services, or there is evidence of pro-poor inequity. This suggests that socioeconomic inequity with respect to GP visits may be vitiated by contacts with practice nurses.

It may also be the case that there is not inequity with respect to GP visits but there is with respect to practice nurse visits.

In this chapter we analyse horizontal inequity in primary care in England accounting for both GP and practice nurse consultation use. We *test* for horizontal inequity by examining the significance and sign of variables that ought not to affect health care use on equity grounds. In addition, we compare the factors associated with practice nurse visits to those associated with GP visits in order to investigate the differences in patient's characteristics that utilise these two types of services. The concentration index approach is used to *measure* the extent of horizontal inequity with respect to income for both GP and practice nurse service utilisation.

3.4. Methods to measuring and explaining horizontal inequity

3.4.1. Testing for and measuring horizontal inequity

The analysis of horizontal inequity (HI) can be broadly categorised into analyses that aim to *test* for or identify horizontal inequity with respect to a number of socioeconomic and equity-relevant indicators, and analyses that aim to *measure* the extent of horizontal inequity with respect to a variable of interest (Abásolo *et al.*, 2001). The first approach consists of regressing health care utilisation against need indicators that ought to affect health care utilisation and non-need indicators that ought not to affect health care use, and examining the significance and sign of variables felt to be non-need variables. Suppose the following utilisation equation:

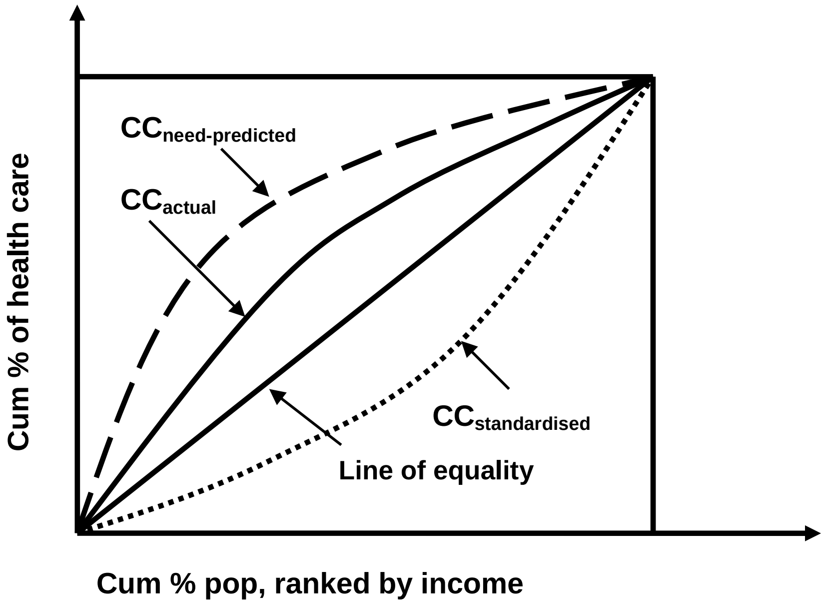
$$q_i = \alpha + \sum_k \beta_k N_{ik} + \sum_j \delta_j Y_{ij} + \varepsilon_i \qquad (3.1)$$

Where q_i measures health care consumption; N_i is a set of k need variables that ought to affect health care use and Y_i is a set of j non-need variables that ought not to affect health care use. Testing for the statistically significant effect of variables thought to be non-need indicators provide the test for horizontal inequity (i.e. there is horizontal inequity when $\delta_j \neq 0$, for any j).

The second approach aimed to *measure* HI focuses on comparing the allocation of health care utilisation across socioeconomic groups, most commonly income groups, after adjusting for differences in their needs. In the recent literature on equity, it has becomes the norm to quantify horizontal inequity in this way using a concentration index approach as proposed by Wagstaff *et al.*, 1991b. This approach allows for the measurement, not only the identification, of the horizontal inequity.

As noted in Chapter 2, concentration indices have a graphical representation by their corresponding concentration curves (CC). In the case of the analysis of equity in health care utilisation, the focus is usually on the allocation of health care use across the socioeconomic or income distribution. In Figure 3.1 the solid line CC_{actual} is the concentration curve of actual use which would lie above (below) the 45 degree line if poorer (richer) individuals receive more than proportional health care. If every individual in the population received the same health care the concentration curve would overlap with the 45 degree line or the line of equality. The CI can be computed as twice the area between the line of equality and the concentration curve, or using the formulae presented in the previous chapter.

Figure 3.1. Concentration curves of health care utilisation



However, finding that the CI of actual use is not zero only tells the analyst something about *inequality*, i.e. different individuals receive different amount of health care, but it tells very little in terms of inequity as we are not taking into account differences in needs in the population. For instance, finding that poorer individuals consume proportionally more health care would not be interpreted as inequity.

Therefore, in order to measure horizontal *inequity*, we are required to standardise by the different levels of needs across individuals. Equation (3.1) can be used as a device to standardise health care utilisation by needs (for the non-need variables we do not want to standardise for, but it would bias the coefficients of the need variables if they were omitted from the regression (Gravelle, 2003)). This method is known as the indirect need-standardisation method. Following Equation (3.1), the need-predicted allocation is defined as,

$$\hat{q}_i = \hat{\alpha} + \sum_k \hat{\beta}_k N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij} + \varepsilon_i \qquad (3.2)$$

Equation (3.2) is thus used to predict how much health care individuals would have received if they had been treated as others with the same need characteristics were, *on average*, treated in the system. The effects of the non-need variables in the prediction are neutralised by setting them equal to their means (or to any other vector of constant). Note that the need-predicted allocation is thus derived based on the effect of the need variables recovered from the regression model. No investigation about the appropriateness of the impact of these estimates is conducted on horizontal equity analyses. Therefore, if the estimated coefficients, $\hat{\beta}_k$, do not provide appropriate variation in health care use with respect to needs (e.g. the coefficients are not significantly different from zero, large enough, or even if these effects lead to more health care use being received by individuals with less needs), the horizontal inequity analysis would not be able to capture this source of inequity.

Continuing with the measurement of horizontal inequity, note that in the case of using a non-linear model for the utilisation equation (as it is likely to be the case given the typical nature of dependent variables in health care utilisation such as non-negative integer counts or binary measures) the effect of the non-need variables cannot be entirely neutralised by setting them equal to any given value as the prediction would depend on the value taken by all the covariates. However, accepting this, non-linear models can be used to create an approximation to the need-standardised health care variable computed as the difference between the actual and the need-predicted health care variable plus the mean of the prediction (in order to ensure that actual and need-standardised health care use have the same mean),

$$\hat{q}_i^{STN} = q_i - G(\hat{\alpha} + \sum_k \hat{\beta}_k N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij}) + \frac{1}{n}\sum_{n=1}^{n} G(\hat{\alpha} + \sum_k \hat{\beta}_k N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij}) \qquad (3.3)$$

Where G(.) would take the form of the non-linear model applied to the health care utilisation equation such as a probit, logit, negative binomial, etc.

Graphically in Figure 3.1 the concentration curve resulting from Equation (3.2), i.e. the need-predicted health care use, is presented by the dashed line $CC_{\text{need-predicted}}$. When the concentration curve of actual use lies below (above) the concentration curve of need-predicted use, there is horizontal inequity favouring the rich (poor). Equivalently, the difference between the 45 degree line and the CC of need-standardised health care utilisation (dotted line in Figure 3.1) directly summarises the extent of horizontal inequity, indicating a pro-rich (pro-poor) distribution when the curve lies below (above) the line of equality.

Horizontal inequity can then be quantified as the difference between the concentration indices of actual and need-predicted health care use with respect to income, or equivalently, as the CI of need-standardised health care use with respect to income[7],

$$HI = 2 * \int [CC_{need-predicted} - CC_{actual}] = CI_q - CI_{\hat{q}} = CI_{\hat{q}^{STN}} \qquad (3.4)$$

This index lies between -1 and +1, with a positive (negative) value indicating pro-rich (pro-poor) income-related horizontal inequity, i.e. the rich (poor) have higher than expected use given their level of need. Similarly to the previous chapter, our measures of health service use are also bounded between zero and one, and thus measures of horizontal inequity using the standard concentration index would be affected by the mean dependency problem. Therefore we applied the correction proposed by Erreygers, 2009.

[7] Due to the approximation required in the context of non-linear utilisation models, the results based on the difference between the concentration indices of actual and need-predicted health care use and the results using the standardisation approach might not be identical.

This inequity estimate provides a measure of horizontal inequity 'on balance' (Wagstaff & van Doorslaer, 2000) in the sense that if there is pro-poor horizontal inequity in one part of the distribution and pro-rich horizontal inequity in another part of the distribution then the CC of actual and need-predicted allocation will cross. The index would then be reduced by compensating inequity in favour of one group in one part of the distribution with inequity in favour of the other group in the other part of the distribution.

Bootstrapping techniques have been used in the literature to derive standard errors (SEs) around the contributor factors in decomposition analysis of CIs (van Doorslaer et al., 2004). However, statistical inferences on the significance of the horizontal inequity estimates have commonly been derived by looking at the SEs around the CI of the need-standardised allocation of health care, which provides the measure of HI as defined in Equation (3.3). This is achieved by using the 'convenient regression' method explained in Chapter 2 to derived SEs around concentration indices estimates. The methods traditionally employed allow correcting SEs for cluster design and adjust for sample weights, or autocorrelation, but they ignore the extra uncertainty introduced by the fact that the need-predicted variable is derived from the predicted values of a regression model. In this chapter, we propose to use bootstrapping techniques based on 200 replications to compute SEs around the estimates of HI. The regression model used to derive the need-predicted allocation of health care, defined in Equation (3.2), is included in the bootstrapping process in order to account for the uncertainty introduced by the model estimation.

3.4.2. Decomposing inequality in health care utilisation

The estimates of inequality can be decomposed based on one property of the concentration index shown in Chapter 2 for the case of inequalities in health. Recall that Wagstaff *et al.*, 2003 have shown that based on an additive linear regression model of health, the inequality indices can be decomposed by the contribution of each explanatory factor. However, in the context of the analysis of equity in health care utilisation, the dependent variables are typically defined as non-linear variables (such as binary outcomes, as analysed in this study). The decomposition results for a non-linear model of health care hold if some linear approximation to the non-linear model is made, by for instance, estimating the marginal effects (van Doorslaer *et al.*, 2004). For a nonlinear functional form $G(.)$, the model for health care would be given by,

$$q_i = G(\hat{\alpha} + \sum_k \hat{\beta}_k N_{ik} + \sum_j \hat{\delta}_j Y_{ij} + \varepsilon_i) = \alpha + \sum_k \beta_k^m N_{ik} + \sum_j \delta_j^m Y_{ij} + u_i \qquad (3.5)$$

Where $\beta^m{}_k$ and $\delta^m{}_j$ are the estimated marginal effects. The decomposition result can be applied such as,

$$CI = \sum_k (\frac{\beta_k^m \overline{N}_k}{\overline{q}}) CI_k + \sum_j (\frac{\delta_j^m \overline{Y}_j}{\overline{q}}) CI_j + \frac{GC_u}{\overline{q}} \qquad (3.6)$$

where μ is the mean of q; $\overline{N}$ is the mean of the need variables, $\overline{Y}$ is the mean of the non-need variables; CI_k, CI_j are the concentration index of N, Y variables with respect to income, respectively; and GC_ε is the generalised concentration index for the error term.

Van Doorslaer *et al.*, 2004 have shown how the concentration index for need-standardised utilisation is equal to that which is obtained by subtracting the contributions of all need variables from the concentration index of actual health care. Horizontal inequity could thus be computed as the difference between the concentration index of actual health care allocation minus the contribution of the need variables. However, when using non-linear models the results based on the decomposition are generally not identical to those that are obtained by alternative methods such as the standardisation technique. The reason being that the former approach relies on an approximation in order to compute the marginal effects[8]. However, in the majority of cases the results are similar (van Doorslaer *et al.*, 2004), and looking at the approximate contributions of each of the explanatory factors provides some useful insights into the direction and magnitude of the various sources of inequity in health care. In some cases, linear probability models can be used, which avoids the approximation in order to compute marginal effects, but they introduce other problems, namely that they can lead to predicted probabilities of use lying outside the range zero to one.

[8] Note that, in addition, marginal effects are commonly evaluated at particular values of the other covariates (typically the sample mean), and the results of the decomposition may change if alternative values are used. In this chapter, we estimate the marginal effects computing the average of the marginal effects of each observation using their specific covariates values rather than the marginal effect evaluated at the sample means.

As noted above, we apply the correction proposed by Erreygers, 2009 to the concentration index measures and the decomposition of the CI still holds when using this correction. While bootstrapping techniques are used to derive standard errors around the equity point estimates, the considerable computational demands for deriving the marginal effects of the models precluded the use of bootstrapping techniques to assess the statistical significance of the contribution of the covariates in the models in the decomposition analyses[9]. Therefore, while we compute the magnitude of the contribution of each covariate to the observed inequality in health care use, no inference is made about the statistical significance of the contribution of the individual covariates.

3.5. Exploring horizontal inequity in primary care services using the Health Survey for England

3.5.1. Data

This analysis is based on pooled data from two rounds (2001, 2002) of the Health Survey for England (HSE) (National Centre for Social Research and University College London) described in the previous chapter. We linked the individual level data in the HSE to data on area supply characteristics available at the Health Authority (HA) of residence level. The supply variables were taken from the 2001 General Medical Statistics database (Information Centre for Health and Social Care, 2008b) and the AREA database (Sutton *et al*., 2002; Gravelle *et al.*, 2003). In 2001 and 2002 England was divided into 95 Health Authorities, which in 2001 had a mean population of 515,517 residents (range 168,873 to 1,050,626).

3.5.2. Practice nurse and GP visits

We use data for 2001 and 2002 because in these years there are questions in the HSE about both types of visit for the whole sample. Individuals were asked '*during the last two weeks ending yesterday, did you see a practice nurse at the GP surgery on your own behalf?'*, and if so, how many times. They were asked similar questions about GP consultations. Very few respondents had more than one visit to see either the practice nurse or the GP (0.6% and 3% of the sample, respectively) and so we measure use as

[9] We run simultaneous equation models using a bivariate probit framework on an expanded sample of over 300,000 observations. The sample was expanded to account for the probability of being selected in the bootstrapping process. The computation of the marginal effects after this process and in this sample takes over a day for a single iteration, which precludes the inference of the statistical significance of the contribution of the individual covariates to the inequality in health care.

a binary variable reflecting whether or not the respondent visited each professional in the previous two weeks. The small sample size of individuals receiving more than one visit also precluded the analysis of conditional utilisation (i.e. the number of visits for those who had at least one visit).

3.5.3. Need variables

We hypothesise that health care use will be determined by need variables and by other 'non-need' variables that might affect health care use but which ideally ought not to. Classifying variables as need or non-need variables requires making value judgements about which factors ought to affect use and which factors ought not to (Gravelle *et al.*, 2006). For instance, if one believes that health care use should only be determined by health status, demographic indicators such as age or gender might be regarded as non-need factors. Alternatively, the analyst may consider age and gender indicators to have a legitimate effect on utilisation capturing variations in health care needs not reflected on generic measures of health status (Sutton, 2002). In principle, socioeconomic and supply indicators would generally be categorised as non-need indicators. However, if the included need measures are not capable of fully capturing variation in needs for health care, these indicators might act as a proxy for unobserved need variables. Including a comprehensive set of need measures capturing morbidity and severity levels is thus crucial in order to draw conclusion about horizontal inequity.

In practice, empirical analyses of health service use have commonly classified socioeconomic variables including ethnicity as non-need indicators (van Doorslaer *et al.*, 2004; Morris *et al*., 2005), and the common practice involves using data on age, gender and morbidity indicators as need measures. Ideally, measures of capacity to benefit from health care services would be used, however that data is in most cases not available and therefore capacity to benefit is proxied by these health indicators, assuming that lower levels of health are related with higher capacity to benefit from using health care. Therefore we use health status as the measure of needs assuming that individuals with worse health are in higher needs for treatment and have a higher capacity to benefit from it. In this study, age, gender and a comprehensive set of health status indicators are categorised as need factors, and socioeconomic and supply characteristics are thought to be non-need indicators, after controlling for individual need characteristics.

The need variables included in the variable selection process are: gender; a cubic function of individual age; interactions between age and gender, self-assessed general health measured on a five-point scale from very good to very bad health; whether or not the individual has one of 14 longstanding illnesses by broad disease category; the number of longstanding illnesses; whether or not longstanding illness limits the activity of the respondent in any way; GHQ-12 score; acute ill health (measured by the number of days the respondent had to cut down on their usual activities in the previous two weeks because of illness or injury, and whether or not the respondent is prevented from looking for work by temporary sickness or injury); and, chronic ill health (measured by whether or not the individual is permanently unable to work because of long-term sickness or disability).

3.5.4. Non-need variables

We measure socioeconomic status in a number of dimensions: log-transformed equivalised annual household income; social class of head of household (measured in seven categories); highest education qualification (seven categories); economic activity (nine categories); car ownership in household (four categories); ethnicity (eight categories); housing tenure (five categories); marital status (five categories); number of infants aged 0–1 years (2 categories); number of children 2–16 years (5 categories); and, degree of urbanisation (3 categories).

We estimate the continuous income variable using the same approach as explained in Chapter 2, i.e. based on an interval regression model of income bands against a number of individuals and household socioeconomic characteristics. We also include three HA-level supply indicators in the variable selection process: GPs per 1,000 registered patients, practice nurses per 1,000 registered patients; and, the mean distance to registered general practice. The latter is a measure of both GP and practice nurse supply.

HSE year indicator, 11 month of interview indicators to account for monthly trends, plus an indicator to account for whether information for children was obtained from a proxy respondent are included as control variables in the regression model.

3.5.5. Statistical analysis

We estimate the determinants of individual practice nurse and GP visits using a bivariate probit regression model. This model allows us to estimate the determinants of both practice nurse visits and GP visits simultaneously, accounting for any correlation between the error terms of the equations for each type of visit. The bivariate probit model is a seemingly unrelated regression technique that does not include any cross-equation restrictions (i.e., the same set of covariates is included in both equations). Let *P* (*G*) be a binary variable taking the value one if the individual visited the practice nurse (GP) in the previous two weeks and zero otherwise. Suppose that *P* and *G* are both linear functions of need variables *N*, and non-need variables *Y,*

$$P_i = a_0 + a_1 N_i + a_2 Y_i + u_{Pi} \tag{3.7}$$

$$G_i = b_0 + b_1 N_i + b_2 Y_i + u_{Gi} \tag{3.8}$$

where *u* is an error term, *i* indexes individuals and *a* and *b* are parameters to be estimated. One approach to modelling (3.7) and (3.8) is to estimate them separately using, e.g., probit models. This assumes that practice nurse visits and GP visits are independent. An alternative, less restrictive, model, which allows for the two types of visit to be correlated is a bivariate probit model:

$$\begin{aligned} P_i* &= \alpha_0 + \alpha_1 N_i + \alpha_2 Y_i + \mu_{Pi} \\ G_i* &= \beta_0 + \beta_1 N_i + \beta_2 Y_i + \mu_{Gi} \\ E[\mu_P] &= E[\mu_G] = 0 \\ Var[\mu_P] &= Var[\mu_G] = 1 \\ Cov[\mu_P, \mu_G] &= \rho \end{aligned} \tag{3.9}$$

where $P*$ is an unobserved latent variable such that $P* \geq 0$ if $P = 1$ and $P* < 0$ if $P = 0$, and $G*$ is defined similarly. μ is an error term and α and β are coefficients. ρ is the correlation between the error terms in the practice nurse visit and GP visit equations. If $\rho = 0$ then practice nurse visits and GP visits are independent and it is appropriate to use two separate (e.g., probit) models. If $\rho \neq 0$ then practice nurse visits and GP visits are correlated and the equations should be estimated simultaneously using a bivariate probit model.

We investigate whether or not each variable has the same impact on the probability of seeing a practice nurse as on the probability of seeing a GP by testing whether or not the coefficients on *N* and *Y* are the same in Equation (3.9) (i.e., whether or not $\alpha_j = \beta_j$ for *j* = 1,2) using a Wald test. We do this for every individual indicator and jointly for groups of indicators. Additionally, we test for the equality of the marginal effects rather than the equality of the coefficients which led in most cases to the same conclusions (results presented in Appendix 3.1). This was undertaken by using the standard errors around the marginal effects derived using – margins – command in Stata.

From our original starting set of covariates we reduce the model to include only statistically significant variables. We retained variables that were significant in at least one of the equations in order to identify differences in the factors that affect each type of visit. We test for multicollinearity among the variables included in the model using variance inflation factors (VIFs) (Chatterjee & Hadi, 2006).

To maximise the sample size we imputed missing values. Missing values for income were imputed using the linear prediction from a regression of income on the other covariates. For binary and categorical variables, missing values were assigned to the omitted category. To allow for the possibility that items were not missing at random we included dummy variable for all imputed items to indicate item non response.

3.6. Empirical results

The total sample size was 38,025 (19,632 in 2001, 18,393 in 2002). Variable definitions and summary statistics for all the variables included in the analysis are in Table 3.1. Six percent of the sample reported at least one practice nurse visit in the previous two weeks; 15% had at least one GP visit. Four percent saw only the practice nurse, 13% saw only the GP, 81% saw neither, and 2% saw both.

The regression model contains over 100 variables. Other than in the case of the six age variables there was no evidence of multicollinearity problems: the largest VIF was 9.73 and the mean of all the VIFs was 1.64. We present the results for different set of variables in Tables 3.2–3.5. We report the coefficients, z scores and marginal effects for each variable; the last column of each table shows the results of the tests of whether or not the coefficient is statistically significantly different between both types of visit.

Table 3.1. Sample-weighted summary statistics (n = 38,025)

Variable	Mean	Std.Dev.	Variable	Mean	Std.Dev.	Variable	Mean	Std.Dev.
Health service utilisation			***No. longstanding illnesses***			Looking after the home	0.080	0.272
Practice nurse visit in last two	0.062	0.241	0	0.599	0.490	Waiting to take up paid job	0.002	0.048
GP visit in last two weeks	0.149	0.356	1	0.255	0.436	Looking for paid job	0.015	0.122
Age and gender variables			2	0.099	0.299	Doing something else	0.003	0.050
Female	0.541	0.498	3	0.031	0.174	***Ethnic group***		
Age (years/100)	0.385	0.234	4 or more	0.015	0.120	White	0.917	0.275
Health variables			*Permanent long term sickness*	0.032	0.177	Black Caribbean	0.013	0.113
Self-reported general health			*Temporary sickness or injury*	0.003	0.052	Black African	0.010	0.097
Very good	0.380	0.485	***GHQ-12 score***			Indian	0.017	0.131
Good	0.402	0.490	0	0.444	0.497	Pakistani	0.014	0.118
Fair	0.160	0.367	1	0.109	0.312	Bangladeshi	0.005	0.073
Bad	0.044	0.206	2	0.060	0.238	Chinese	0.003	0.050
Very bad	0.013	0.115	3	0.036	0.186	Other	0.021	0.142
Limiting longstanding illness	0.222	0.416	4	0.024	0.154	***Marital status***		
Acute ill health in last fortnight			5	0.020	0.140	Married	0.421	0.494
0 days	0.842	0.365	6	0.016	0.124	Single	0.428	0.495
1-3 days	0.054	0.226	7	0.013	0.112	Separated	0.020	0.140
4-6 days	0.026	0.159	8	0.010	0.097	Divorced	0.062	0.242
7-13 days	0.025	0.155	9	0.008	0.088	Widowed	0.068	0.252
14 days	0.053	0.223	10	0.008	0.088	***No. infants age 0-1 years***		
Longstanding illness			11	0.006	0.078	0	0.912	0.283
Neoplasms & benign growths	0.014	0.119	12	0.006	0.080	1 or more	0.088	0.283
Endocrine & metabolic	0.046	0.209	**Socioeconomic variables**			***No. children aged 2-16 years***		
Mental disorders	0.027	0.162	***Log Income***	9.766	0.916	0	0.566	0.496
Nervous system	0.033	0.180	***Highest education***			1	0.161	0.367
Eye complaints	0.022	0.147	Degree	0.118	0.322	2	0.181	0.385
Ear complaints	0.023	0.151	Higher education less than	0.085	0.280	3	0.067	0.251
Heart & circulatory	0.097	0.296	A level or equivalent	0.096	0.294	4 or more	0.025	0.156
Respiratory system	0.096	0.295	GCSE or equivalent	0.180	0.384	***Degree of urbanisation***		
Digestive system	0.041	0.199	CSE or equivalent	0.043	0.203	Rural	0.232	0.422
Genito-urinary	0.017	0.131	Other qualification	0.036	0.187	Suburban	0.591	0.492
Skin complaints	0.025	0.155	No qualification	0.211	0.408	Urban	0.177	0.382
Musculo-skeletal	0.155	0.362	***Economic activity***			**Supply variables**		
Infectious disease	0.002	0.048	In paid employment	0.424	0.494	Mean distance to General Practice	1.209	6.020
Blood & related organs	0.006	0.075	Going to school/college full	0.042	0.200	No. practices nurses per 1000 patients	0.219	0.036
Other complains	0.002	0.042	Retired from paid work	0.169	0.375	No. GPs per 1000 patients	0.560	0.048

The correlation coefficient between the error terms in the practice nurse and GP supply equations, ρ, is positive and significant (ρ=0.31, Wald test of ρ=0: χ^2=315.079, $p < 0.001$). Therefore, the bivariate probit model is preferred. This result means that unobservable factors that are positively correlated with practice nurse visits are positively related with GP visits. This suggests that practice nurse services complement GP services with respect to the unobserved characteristics, for example by providing follow-up care to patients with these characteristics.

3.6.1. Effect of the need variables in primary care services

We start by discussing the effect of the need variables in primary care utilisation. The coefficient of the need indicators are usually not reported or discussed in the evaluations of horizontal inequity. As Gravelle *et al.*, 2006 pointed out, this is a pity because some useful insights can be derived from the effect of the need factors on health care utilisation. In our analysis, we focus on the differences between the health characteristics of patients visiting a GP and that of patients visiting a practice nurse.

There is a non-linear (broadly u-shaped) association between age and primary care visits, which varies significantly by gender and by type of visit (Figure 3.1; Table 3.2). Individuals at all ages are significantly more likely to see the GP than the practice nurse, all else equal, and the best-fitted line plotting the probability of each type of visit against age is slightly flatter for practice nurses than for GPs. This suggests that there is less variation in practice nurse visits by age.

Table 3.3 presents the results for the health variables. The effect of self-assessed general health is significant, with individuals reporting worse health having a higher probability of using both GP and practice nurse services. However, the probability of seeing a practice nurse among those reporting “very bad” health is not significantly different from those reporting “very good” health. This may be due to individuals with very poor health being treated by other health care professionals, such as GPs. Individuals who cut down on their normal activities due to illness or injury over the last two weeks had a higher probability of visiting the practice nurse, just as they do for seeing a GP. However, the marginal effects of acute ill health are significantly more positive for GP visits, suggesting that acute illness has a significantly greater effect on the likelihood of a GP visit than a nurse visit.

Table 3.2. Partial effect of age and gender variables with practice nurse and GP

	Nurse visit			GP visit				
Variables	Coef.	z	ME	Coef.	z	ME	Coef. Nurse = Coef. GP	
Female	-0.342	-4.29	-0.038	-0.166	-2.97	-0.034	χ^2 = 3.77	p = 0.0521
Age	-10.463	-9.41	-1.170	-7.997	-10.54	-1.638	χ^2 = 3.51	p = 0.0609
Age squared	22.518	8.75	2.518	15.830	8.74	3.242	χ^2 = 4.79	p = 0.0286
Age cubed	-13.422	-7.32	-1.501	-9.035	-6.81	-1.850	χ^2 = 4.02	p = 0.0450
Female*age	5.305	5.98	0.593	3.847	5.95	0.788	χ^2 = 2.04	p = 0.1528
Female*age squared	-12.486	-5.11	-1.396	-9.265	-5.08	-1.898	χ^2 = 1.29	p = 0.2557
Female*age cubed	7.912	4.18	0.885	5.788	4.04	1.185	χ^2 = 0.93	p = 0.3355
Tests of joint restrictions								
Age and gender = 0	χ^2 = 123.07 p < 0.0001			χ^2 = 179.83 p < 0.0001			χ^2 = 17.96	p = 0.0122

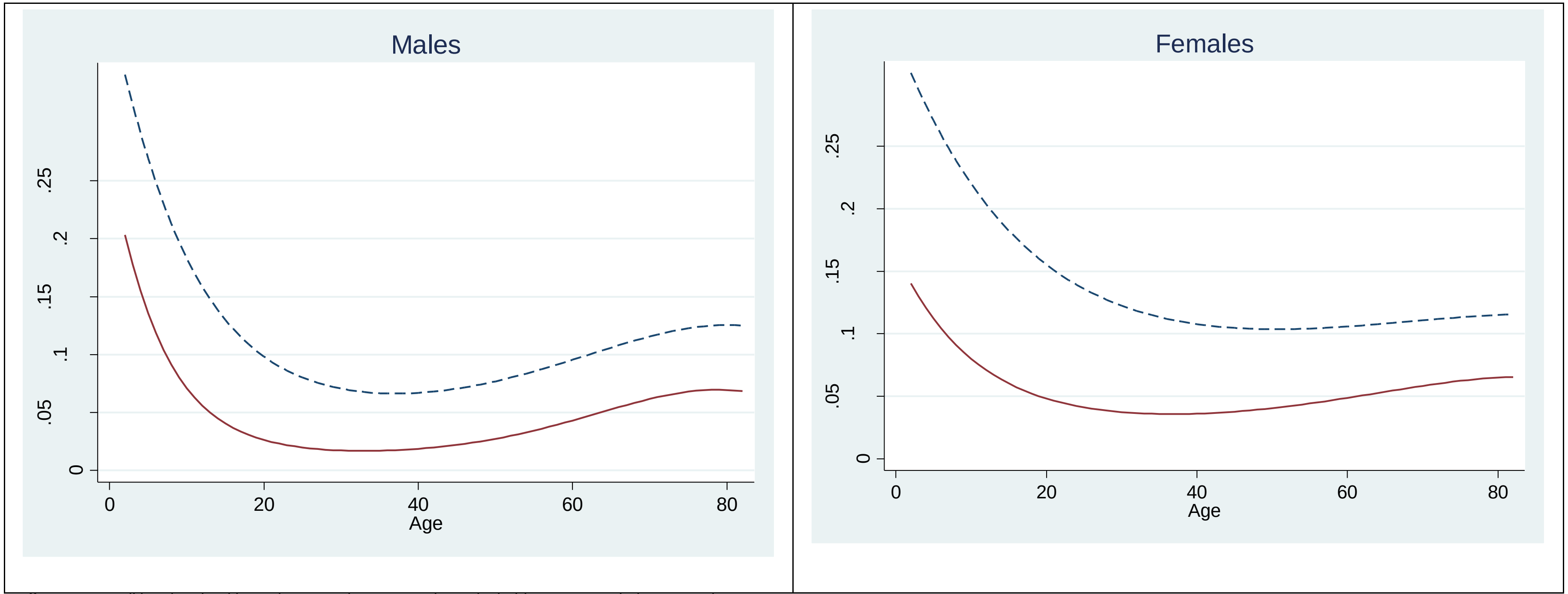
Health variables, socioeconomic variables and supply variables are also included and reported in other tables. The models also control for year of data, proxy responses, month of the interview and missing values. Individual sample weights are used throughout. The standard errors are adjusted for clustered sampling at the primary sampling unit level.

Five longstanding illnesses are significant and positively correlated with practice nurse visits; while a broader range of conditions are correlated with GP use. The following longstanding illnesses are positively correlated with visiting a practice nurse (the last two are weakly so): endocrine and metabolic disorders, diseases of the heart and circulatory system, respiratory system, neoplasms and benign growths and of the genitourinary system. In addition to those (with the exemption of neoplasm and benign growths), GP services also play a significant role for patients with mental disorders, digestive problems, skin complains and musculoskeletal conditions (the last one weakly so). Those with chronic illness, as measured by those who are inactive due to long-term illness or disability, have a significantly higher probability of seeing a practice nurse and the probability that they see a GP is negative and non-significant. The opposite hold true in the case of GHQ-12 scores, which are significant and positively correlated with GP visits, while they are not significantly correlated with practice nurse visits.

3.6.2. Testing for horizontal inequity

We test for horizontal inequity by looking at the effect of socioeconomic and supply characteristics after controlling for need factors. Table 3.4 presents the results for the socioeconomic variables. We start by discussing the effect of the socioeconomic and supply indicators on the nurse use model. Income has a negative but non-significant effect, while the education variables are jointly significant; those with education attainment lower than a degree are more likely to see a practice nurse, all else equal.

Figure 3.2. Conditional effects of age and gender on practice nurse (solid lines) and GP visits (dashed lines).



Effects are conditional on health, socioeconomic status and supply, held constant at their mean values.

Table 3.3. Partial effect of health variables with practice nurse and GP visits.

	Nurse visit			GP visit				
Variables	**Coef.**	**z**	**ME**	**Coef.**	**z**	**ME**	**Coef. Nurse = Coef. GP**	
Self-reported general health								
Very good	Base category			Base category				
Good	0.107	3.39	0.012	0.153	6.52	0.031	$\chi^2 = 1.54$	$p = 0.2145$
Fair	0.208	5.00	0.023	0.338	10.27	0.069	$\chi^2 = 6.77$	$p = 0.0093$
Bad	0.223	3.44	0.025	0.321	6.10	0.066	$\chi^2 = 1.58$	$p = 0.2083$
Very bad	0.132	1.36	0.015	0.448	5.69	0.092	$\chi^2 = 7.26$	$p = 0.0070$
Acute ill health (days cut down)								
0 days	Base category			Base category				
1-3 days	0.098	1.83	0.011	0.483	13.18	0.099	$\chi^2 = 37.95$	$p < 0.0001$
4-6 days	0.233	3.68	0.026	0.737	14.48	0.151	$\chi^2 = 42.18$	$p < 0.0001$
7-13 days	0.264	4.01	0.030	0.919	19.04	0.188	$\chi^2 = 63.10$	$p < 0.0001$
14 days	0.213	4.28	0.024	0.743	18.90	0.152	$\chi^2 = 77.99$	$p < 0.0001$
Longstanding illness								
Neoplasms & benign	0.168	1.93	0.019	0.069	0.87	0.014	$\chi^2 = 0.84$	$p = 0.3605$
Endocrine & metabolic	0.359	6.68	0.040	0.221	4.76	0.045	$\chi^2 = 4.63$	$p = 0.0315$
Mental disorders	0.116	1.56	0.013	0.229	3.99	0.047	$\chi^2 = 1.62$	$p = 0.2028$
Nervous system	-0.158	-2.26	-0.018	0.057	1.08	0.012	$\chi^2 = 6.70$	$p = 0.0096$
Heart & circulatory	0.263	5.42	0.029	0.165	4.19	0.034	$\chi^2 = 2.67$	$p = 0.1024$
Respiratory system	0.123	2.81	0.014	0.093	2.82	0.019	$\chi^2 = 0.35$	$p = 0.5536$
Digestive system	0.040	0.67	0.005	0.165	3.39	0.034	$\chi^2 = 3.13$	$p = 0.0770$
Genitourinary system	0.149	1.80	0.017	0.274	4.05	0.056	$\chi^2 = 1.71$	$p = 0.1914$
Skin complaints	0.108	1.45	0.012	0.228	4.21	0.047	$\chi^2 = 1.85$	$p = 0.1737$
Musculoskeletal	-0.008	-0.20	-0.001	0.065	1.91	0.013	$\chi^2 = 2.10$	$p = 0.1472$
No. longstanding illnesses								
0 or 1	Base category			Base category				
2	0.006	0.11	0.001	-0.068	-1.59	-0.014	$\chi^2 = 1.35$	$p = 0.2455$
3	-0.144	-1.68	-0.016	-0.177	-2.60	-0.036	$\chi^2 = 0.10$	$p = 0.7539$
4 or more	-0.100	-0.83	-0.011	-0.264	-2.68	-0.054	$\chi^2 = 1.24$	$p = 0.2647$
Permanent sickness	0.193	2.81	0.022	-0.018	-0.29	-0.004	$\chi^2 = 6.27$	$p = 0.0113$
Temporary sickness	0.252	1.27	0.028	0.138	0.84	0.028	$\chi^2 = 0.20$	$p = 0.6533$
GHQ-12 scores								
0	Base category			Base category				
1	0.052	1.26	0.006	0.106	3.18	0.022	$\chi^2 = 1.22$	$p = 0.2702$
2	0.011	0.21	0.001	0.112	2.71	0.023	$\chi^2 = 2.72$	$p = 0.0992$
3	-0.062	-0.95	-0.007	0.171	3.35	0.035	$\chi^2 = 9.01$	$p = 0.0027$
4	-0.031	-0.39	-0.003	0.153	2.51	0.031	$\chi^2 = 3.87$	$p = 0.0493$
5	0.007	0.09	0.001	0.243	3.80	0.050	$\chi^2 = 5.62$	$p = 0.0178$
6	-0.026	-0.28	-0.003	0.272	3.99	0.056	$\chi^2 = 7.14$	$p = 0.0075$
7	0.105	1.02	0.012	0.199	2.43	0.041	$\chi^2 = 0.69$	$p = 0.4047$
8	0.079	0.68	0.009	0.421	4.90	0.086	$\chi^2 = 5.89$	$p = 0.0148$
9	0.151	1.27	0.017	0.163	1.67	0.033	$\chi^2 = 0.01$	$p = 0.9372$
10	-0.068	-0.50	-0.008	0.243	2.46	0.050	$\chi^2 = 3.79$	$p = 0.0515$
11	0.203	1.49	0.023	0.323	2.92	0.066	$\chi^2 = 0.65$	$p = 0.4185$
12	0.048	0.35	0.005	0.423	3.73	0.087	$\chi^2 = 4.11$	$p = 0.0426$
Tests of joint								
Self-reported general	$\chi^2 = 26.95$ $p < 0.0001$			$\chi^2 = 115.53$ $p < 0.0001$			$\chi^2 = 10.99$	$p = 0.0267$
Acute ill-health	$\chi^2 = 39.12$ $p < 0.0001$			$\chi^2 = 807.82$ $p < 0.0001$			$\chi^2 = 166.10$	$p < 0.0001$
Longstanding illness	$\chi^2 = 93.73$ $p < 0.0001$			$\chi^2 = 66.20$ $p < 0.0001$			$\chi^2 = 33.08$	$p = 0.0003$
No. longstanding	$\chi^2 = 5.05$ $p = 0.1678$			$\chi^2 = 9.38$ $p = 0.0247$			$\chi^2 = 2.23$	$p = 0.258$
GHQ-12 scores	$\chi^2 = 8.71$ $p = 0.7277$			$\chi^2 = 79.07$ $p < 0.0001$			$\chi^2 = 28.65$	$p = 0.0044$

Age and gender variables, socioeconomic variables and supply variables are also included and reported in other tables. The models also control for year of data, proxy responses, month of the interview and missing values. Individual sample weights are used throughout. The standard errors are adjusted for clustered sampling at the primary sampling unit level.

Table 3.4. Partial effect of socioeconomic variables with practice nurse and GP.

Variables	Nurse visit			GP visit			Coef. Nurse = Coef.	
	Coef.	z	ME	Coef.	z	ME		
Income (log)	-0.008	-0.44	-0.001	-0.019	-1.64	-0.004	χ^2 = 0.30	p= 0.584
Education qualification								
Degree	Base category			Base category				
Less than degree	0.081	1.42	0.009	0.038	0.82	0.008	χ^2 = 0.37	p= 0.544
A level or equivalent	0.154	2.79	0.017	0.066	1.49	0.013	χ^2 = 1.71	p= 0.191
GCSE or equivalent	0.079	1.54	0.009	0.092	2.42	0.019	χ^2 = 0.05	p= 0.820
CSE or equivalent	0.000	0.00	0.000	0.090	1.63	0.018	χ^2 = 1.18	p= 0.277
Other qualification	0.157	2.20	0.018	0.141	2.37	0.029	χ^2 = 0.03	p= 0.858
No qualification	0.049	0.92	0.005	0.096	2.33	0.020	χ^2 = 0.55	p= 0.458
Economic activity								
In paid employment	Base category			Base category				
Going to school/college full	-0.103	-1.33	-0.011	-0.267	-4.82	-0.055	χ^2 = 3.22	p= 0.073
Retired from paid work	0.031	0.60	0.004	-0.006	-0.14	-0.001	χ^2 = 0.35	p= 0.553
Looking after the home	0.124	2.58	0.014	0.027	0.68	0.005	χ^2 = 2.73	p= 0.099
Waiting to take up paid job	0.156	0.57	0.017	-0.006	-0.03	-0.001	χ^2 = 0.23	p= 0.634
Looking for paid job	0.087	0.82	0.010	-0.141	-1.72	-0.029	χ^2 = 3.73	p= 0.054
Doing something else	0.290	1.38	0.032	-0.028	-0.16	-0.006	χ^2 = 1.39	p= 0.239
Ethnic group								
White	Base category			Base category				
Black Caribbean	-0.005	-0.04	-0.001	0.102	1.28	0.021	χ^2 = 0.61	p= 0.436
Black African	0.071	0.53	0.008	0.049	0.52	0.010	χ^2 = 0.02	p= 0.889
Indian	-0.043	-0.39	-0.005	-0.013	-0.17	-0.003	χ^2 = 0.07	p= 0.790
Pakistani	0.043	0.38	0.005	0.312	3.68	0.064	χ^2 = 4.08	p= 0.044
Bangladeshi	-0.073	-0.34	-0.008	0.113	0.85	0.023	χ^2 = 0.75	p= 0.386
Chinese	-0.419	-1.61	-0.047	-0.111	-0.50	-0.023	χ^2 = 1.13	p= 0.289
Other	-0.108	-1.09	-0.012	0.122	1.93	0.025	χ^2 = 3.90	p= 0.048
Marital Status								
Married	Base category			Base category				
Single	-0.132	-2.61	-0.015	-0.126	-3.22	-0.026	χ^2 = 0.01	p= 0.918
Separated	-0.011	-0.13	-0.001	0.021	0.29	0.004	χ^2 = 0.09	p= 0.769
Divorced	-0.054	-1.05	-0.006	0.059	1.41	0.012	χ^2 = 3.26	p= 0.071
Widowed	-0.074	-1.43	-0.008	-0.060	-1.29	-0.012	χ^2 = 0.05	p= 0.828
No. infants age 0-1 years								
0	Base category			Base category				
1 or more	0.073	1.56	0.008	0.120	3.40	0.025	χ^2 = 0.82	p= 0.367
No. children aged 2-16								
0	Base category			Base category				
1	-0.091	-2.06	-0.010	0.042	1.38	0.009	χ^2 = 7.00	p= 0.008
2	-0.092	-1.81	-0.010	-0.035	-0.97	-0.007	χ^2 = 0.99	p= 0.319
3	-0.078	-1.14	-0.009	-0.072	-1.47	-0.015	χ^2 = 0.01	p= 0.941
4 or more	-0.130	-1.15	-0.015	-0.166	-2.29	-0.034	χ^2 = 0.08	p= 0.774
Degree of urbanisation								
Rural	Base category			Base category				
Suburban	-0.091	-2.69	-0.010	0.014	0.58	0.003	χ^2 = 7.51	p= 0.006
Urban	-0.068	-1.52	-0.008	-0.001	-0.03	0.000	χ^2 = 1.76	p= 0.185
Tests of joint restrictions								
Education = 0	χ^2 = 12.90 p = 0.0446			χ^2 = 9.36 p = 0.1544			χ^2 = 7.30	p= 0.294
Economic activity = 0	χ^2 = 18.65 p = 0.0169			χ^2 = 28.34 p = 0.0004			χ^2 = 13.59	p= 0.093
Ethnic group = 0	χ^2 = 3.72 p = 0.8115			χ^2 = 18.76 p = 0.0090			χ^2 = 8.66	p= 0.278
Marital status = 0	χ^2 = 8.54 p = 0.0738			χ^2 = 15.27 p = 0.0042			χ^2 = 3.34	p= 0.053
No. children = 0	χ^2 = 5.53 p = 0.2372			χ^2 = 12.88 p= 0.0119			χ^2 = 8.51	p= 0.075
Degree of urbanisation = 0	χ^2 = 7.25 p = 0.0266			χ^2 = 0.54 p = 0.7644			χ^2 = 7.60	p= 0.022

Age and gender variables, health variables and supply variables are also included and reported in other tables. The models also control for year of data, proxy responses, month of the interview and missing values. Individual sample weights are used throughout. The standard errors are adjusted for clustered sampling at the primary sampling unit level.

Compared with being in paid employment, those looking after the home or family have a significantly greater probability of visiting a practice nurse. Individuals living in suburban areas have a lower probability of seeing a nurse than those living in rural areas. Household composition also influences the probability of seeing a practice nurse. Being single or having children in the household has a negative impact, while having an infant aged 0-2 years increases the probability of visiting a practice nurse. Distance to the practice is negatively correlated with practice nurse use while GP supply is positively correlated with seeing a practice nurse (Table 3.5).

Table 3.5. Partial effect of supply variables with practice nurse and GP visits.

	Nurse visit			GP visit			Coef. Nurse = Coef. GP	
Variables	**Coef.**	**z**	**ME**	**Coef.**	**z**	**ME**		
Mean distance to practice	-0.049	-1.79	-0.005	0.005	0.29	0.001	$\chi^2 = 3.24$	p = 0.0718
GP supply	0.845	2.73	0.094	0.432	2.05	0.089	$\chi^2 = 1.32$	p = 0.2502
Tests of joint restrictions								
Supply = 0	$\chi^2 = 8.32$ p = 0.0156			$\chi^2 = 4.63$ p = 0.0988			$\chi^2 = 3.76$ p = 0.1548	

Age and gender variables, health variables and socioeconomic variables are also included and reported in other tables. The models also control for year of data, proxy responses, month of the interview and missing values. Individual sample weights are used throughout. The standard errors are adjusted for clustered sampling at the primary sampling unit level.

Moving to the results from the GP utilisation model, we find some similarities with the effect of the socioeconomic variables on practice nurse use; education attainment is also significantly and negatively correlated with GP visits, and GP supply and household composition have a similar impact on GP visits as described above. However, the effect of some of the socioeconomic variables differs from that on the practice nurse model. Table 3.4 shows that, while income does not affect the probability of seeing a practice nurse, it is weakly associated with GP visits; but the effect is not significantly different between the two types of care. Those going to school or college full time and those looking for a paid job are significantly less likely to see the GP, while, individuals in Pakistani and 'Other' ethnic groups are significantly more likely to visit the GP than those in the White group. The effect of these variables on practice nurse visits was found to be non-significant. Finally, with respect to the effect of supply characteristics, we found that the distance to practice significantly decreases the probability of seeing a practice nurse, but it does not affect the probability of visiting the GP (Table 3.5).

3.6.3. Measuring horizontal inequity

The indices of income-related horizontal inequity in GP and practice nurse visits are presented in Table 3.6. Before adjusting for needs, both types of use are significantly concentrated among poorer income groups; as reflected by the negative and significant concentration indices of actual health care utilisation in both services. Despite the significant correlation found between the error terms of GP and practice nurse utilisation models, the results from the univariate probit models and from the bivariate probit model yield to the same horizontal inequity estimates (see Table 3.6).

Table 3.6. Horizontal inequity indices in practice nurse and GP visits use

CI	GP visits		Nurse visits	
	CI	CI/SE	CI	CI/SE
Actual use	-0.0668	-13.63	-0.0234	-6.77
Need-predicted (univariate models)	-0.0542	-22.50	-0.0244	-13.48
Need-predicted (bivariate models)	-0.0542	-18.77	-0.0246	-15.39
HI (univariate probit models)	-0.0126	-2.20	0.0010	0.20
HI (bivariate probit model)	-0.0126	-2.39	0.0011	0.25

Note: CI = concentration index; HI = horizontal inequity; SE = Standard error; SE are computed using bootstrapping techniques.

In the case of GP services, there is pro-poor horizontal inequity, suggesting that after controlling for their levels of needs, GP services are significant and disproportionally concentrated among poorer individuals. The estimate of horizontal inequity in practice nurse utilisation is found to be positive but considerably small and non-significant. The standard errors computed using bootstrapping techniques based on 200 replications were slightly larger than those provided by the SE of the point estimate of the CI of need-standardised allocation (results presented in Appendix 3.2).

3.6.4. Explaining horizontal inequity

The decomposition results are presented in Table 3.7 and 3.8. Table 3.7 summarises the contribution of each of the need variables in explaining health service inequality; while Table 3.8 presents the contribution of the non-need indicators.

Variations in health care utilisation due to variations in needs factors are believed to represent legitimate variation in health care utilisation, and therefore the contribution of these variables are subtracted from the horizontal equity analysis. The analysis of the individual contribution of each of the non-need indicators provides the decomposition of the results of horizontal inequity.

Table 3.7. Decomposition of inequality in health care utilisation (contribution of the need variables)

		Nurse visit				GP visit		
	CI	Cont	Percent	%		Cont	Percent	%
Age	-0.0222	0.0018	-7.80%			0.0016	-2.40%	
Female	-0.0152	0.0273	-116.4%			0.0382	-57.2%	
Age-squared	-0.0538	-0.1100	469.1%			-0.1416	212.0%	
Age-cubed	-0.0953	0.0698	-297.8%			0.0861	-128.9%	
Female*age	-0.0450	-0.0228	97.1%			-0.0302	45.3%	
Female*age-squared	-0.0850	0.0540	-230.2%			0.0733	-109.8%	
Female*age-cubed	-0.1268	-0.0310	132.2%	46.2%		-0.0415	62.2%	21.1%
Good	-0.0029	-0.0001	0.20%			-0.0001	0.20%	
Fair	-0.1678	-0.0025	10.70%			-0.0074	11.10%	
Bad	-0.3071	-0.0014	5.80%			-0.0036	5.40%	
Very bad	-0.3299	-0.0003	1.10%	17.8%		-0.0016	2.40%	19.1%
Neoplasms & benign growths	-0.1334	-0.0001	0.60%			-0.0001	0.20%	
Endocrine & metabolic	-0.1138	-0.0008	3.60%			-0.0009	1.40%	
Mental disorders	-0.2659	-0.0004	1.60%			-0.0013	2.00%	
Nervous system	-0.1163	0.0003	-1.20%			-0.0002	0.30%	
Heart & circulatory	-0.1423	-0.0016	6.90%			-0.0019	2.80%	
Respiratory system	-0.0932	-0.0005	2.10%			-0.0007	1.00%	
Digestive system	-0.0840	-0.0001	0.30%			-0.0005	0.70%	
Genitourinary system	-0.0830	-0.0001	0.40%			-0.0003	0.50%	
Skin complaints	-0.0254	0.0000	0.10%			-0.0001	0.20%	
Musculoskeletal	-0.1128	0.0001	-0.30%	14.1%		-0.0009	1.40%	10.5%
Cutting down activities- 1-3 days	0.0453	0.0001	-0.50%			0.001	-1.40%	
4-6 days	-0.0917	-0.0002	1.10%			-0.0014	2.20%	
7-13 days	-0.1492	-0.0004	1.80%			-0.0028	4.10%	
14 days	-0.1623	-0.0008	3.50%	5.9%		-0.0052	7.80%	12.7%
Number of long-standing illnesses - 2	-0.1412	0.0000	0.20%			0.0008	-1.20%	
3	-0.2150	0.0004	-1.90%			0.001	-1.50%	
4 or more	-0.2621	0.0002	-0.70%	-2.4%		0.0008	-1.20%	-3.9%
GHQ-12 score 1	0.0270	0.0001	-0.30%			0.0003	-0.40%	
GHQ-12 score 2	0.0135	0.0000	0.00%			0.0001	-0.10%	
GHQ-12 score 3	-0.0189	0.0000	-0.10%			-0.0001	0.10%	
GHQ-12 score 4	-0.0592	0.0000	-0.10%			-0.0002	0.30%	
GHQ-12 score 5	-0.0536	0.0000	0.00%			-0.0002	0.30%	
GHQ-12 score 6	-0.0569	0.0000	0.00%			-0.0002	0.30%	
GHQ-12 score 7	-0.0667	0.0000	0.20%			-0.0001	0.20%	
GHQ-12 score 8	-0.1131	0.0000	0.20%			-0.0004	0.60%	
GHQ-12 score 9	-0.0695	0.0000	0.20%			-0.0001	0.10%	
GHQ-12 score 10	-0.1354	0.0000	-0.10%			-0.0002	0.30%	
GHQ-12 score 11	-0.1801	-0.0001	0.40%			-0.0003	0.40%	
GHQ-12 score 12	-0.1023	0.0000	0.10%	0.5%		-0.0002	0.30%	2.4%
Permanent long term sickness	-0.3772	-0.0011	4.50%	4.5%		0.0002	-0.30%	-0.3%
Temporary sickness or injury	-0.4110	-0.0001	0.50%	0.5%		-0.0001	0.20%	0.2%
Total				87.1%				61.8%

Note: CI= Concentration Index; Cont= Contribution; Percent = Percentage contribution

Table 3.8. Decomposition of inequality in health care utilisation (contribution of the non-need variables)

		Nurse visit			GP visit		
	CI	Contr	Percent	%	Contr	Percent	%
Income (log)	0.0453	-0.0015	6.4%	6.4%	-0.0067	10.0%	10.0%
Higher education less than degree	0.1754	0.0005	-2.3%		0.0005	-0.7%	
A level or equivalent	0.1167	0.0008	-3.3%		0.0006	-0.9%	
GCSE or equivalent	0.0396	0.0003	-1.1%		0.0005	-0.8%	
CSE or equivalent	-0.1994	0.0000	0.0%		-0.0006	0.9%	
Other qualification	-0.0576	-0.0001	0.6%		-0.0002	0.4%	
No qualification	-0.2695	-0.0012	5.3%	-0.8%	-0.0045	6.7%	5.6%
Going to school/college full time	-0.1307	0.0002	-1.1%		0.0012	-1.8%	
Retired from paid work	-0.2007	-0.0005	2.0%		0.0002	-0.3%	
Looking after the home	-0.2224	-0.0010	4.2%		-0.0004	0.6%	
Waiting to take up paid job	-0.0444	0.0000	0.0%		0.0000	0.0%	
Looking for paid job	-0.4784	-0.0003	1.2%		0.0008	-1.2%	
Doing something else	-0.2204	-0.0001	0.3%	6.7%	0.0000	0.0%	-2.7%
Black Caribbean	-0.3004	0.0000	0.0%		-0.0003	0.5%	
Black African	-0.2730	-0.0001	0.4%		-0.0001	0.2%	
Indian	-0.0822	0.0000	-0.1%		0.0000	0.0%	
Pakistani	-0.5275	-0.0001	0.6%		-0.0019	2.9%	
Bangladeshi	-0.7171	0.0001	-0.5%		-0.0004	0.5%	
Chinese	0.1202	-0.0001	0.2%		0.0000	0.0%	
Other	-0.1474	0.0001	-0.6%	-0.1%	-0.0003	0.5%	4.5%
Single	-0.0310	0.0008	-3.3%		0.0014	-2.1%	
Separated	-0.0759	0.0000	0.0%		0.0000	0.0%	
Divorced	-0.0461	0.0001	-0.3%		-0.0001	0.2%	
Widowed	-0.2309	0.0005	-2.2%	-5.9%	0.0008	-1.2%	-3.0%
No. infants age 0-1 years	-0.0514	-0.0001	0.6%		-0.0004	0.7%	
No. children aged 2-16 years 1	0.0024	0.0000	0.1%		0.0000	0.0%	
2	-0.0395	0.0003	-1.3%		0.0002	-0.3%	
3	-0.1827	0.0004	-1.8%		0.0007	-1.1%	
4 or more	-0.2880	0.0004	-1.8%	-4.2%	0.0010	-1.5%	-2.2%
Suburban	0.0098	-0.0002	1.0%		0.0001	-0.1%	
Urban	-0.1791	0.0010	-4.1%	-3.1%	0.0000	0.0%	-0.1%
GP supply	-0.0008	-0.0002	0.7%		-0.0002	0.2%	
Mean distance to general practice	0.0001	0.0000	0.1%	0.7%	0.0000	0.0%	0.2%
Total*				-16%			6.5%

Note: *Total percentage contribution of non-need variables includes the contribution of the year indicator, month of the interview, missing values and proxy responses. CI= Concentration Index; Cont= Contribution; Percent = Percentage contribution

In Table 3.7 we observed that around 87% of the estimated inequality across income groups in actual practice nurse service use is explained by demographic and health indicators alone. In the case of GP services, these variables contribute to explaining around 62% of income-related inequalities in GP visits. Therefore, in both cases, most of the variation observed across the income distribution on the probability of using primary care services is due to variation in the need factors. This result highlights the importance of adjusting for needs when investigating horizontal inequities in health service use.

Age and gender make the largest contribution to inequalities in primary care use, followed by self-assessed general health. The presence of long-standing illnesses follows as the next main contributor factor to explain inequalities in practice nurse use, while acute illness measured by number of days cutting down on normal activities plays a larger role in the case of inequalities in GP visits.

Moving to the results of the decomposition of horizontal inequity in practice nurse utilisation, we find that rather than the variable used as ranking measure – i.e., household income, employment status is the non-need indicator playing the largest role on explaining horizontal inequity with almost a 7% contribution to inequalities in practice nurse visits overall.

It is worth noting that although the coefficient of income was found to be negative in the practice nurse service equation, the index of income-related horizontal inequity showed a positive, i.e. pro-rich distribution of practice nurse visits. In both cases the estimates were very small and non-significant; the divergence between the two can be explained by looking at the decomposition results. While the contribution of income to income-related inequalities in practice nurse service use is pro-poor (i.e. consistent with the negative sign of the coefficient in the regression), the size of the contribution is relatively small, just over 6%. Other non-need indicators, such as not being married and having more children in the household, contribute towards a pro-rich allocation of practice nurse visit use as these variables have a negative effect on utilisation and are concentrated on poorer households. The larger pro-rich overall estimate of the sum of the contributions of marital status, household composition, and degree of urbanisation indicators more than compensate for the contribution towards a pro-poor allocation due to income, employment status and supply factors. The decomposition results therefore, shed some light on the mechanism behind the positive estimate of horizontal inequity in practice nurse appointments.

Income contributes to a larger extent to the estimated pro-poor allocation of GP visits, by explaining 10% of the income-related inequality. The next larger contributors towards a pro-poor distribution are education and ethnicity and, to a much lower extent, supply indicators. As with practice nurse use, some non-need indicators contribute towards a more pro-rich allocation. In the case of GP visits, those are marital status, household composition, employment status and degree of urbanisation. Overall, the estimate remains pro-poor in the case of GP visits.

Overall, our models explain 71% and 68% of total income-related inequality in practice nurse and GP service use, respectively. The unexplained variation can be attributed to the residual term, however, note that the residual factors include both a prediction error and an error generated by the linear approximation to obtain the marginal effects (van Doorslaer *et al*., 2004). Therefore, in a non-linear setting it is difficult to estimate the fraction of the error contribution that is due to unmeasured factors.

3.7. Discussion and implications for further work

In this chapter we have presented the methods commonly used in the literature for the identification and measurement of horizontal inequity, and applied them to the investigation of horizontal inequity in primary care services utilisation in England. Unlike previous studies, which focus on GP service use only, we consider GP and practice nurse use, and allow these types of use to be correlated. The findings of this study suggest that the dimensions in which horizontal inequity is observed in GP services in favour of relatively poorer groups do not translate into inequity in practice nurse services use.

This result indicates that it is difficult to draw conclusions about the extent of primary care inequity based only on analyses of GP visits because practice nurses and GPs see different types of patient; inequities in the use of one type of care may be offset by the other type of care. The detailed exploration of the determinants of practice nurse and GP use showed that socioeconomic and supply variables affect the probability of practice nurse and GP visits differently. Individuals who are not in paid employment are less likely to visit their GP, all else equal, but this does not affect the probability of seeing a practice nurse. This suggests that inequalities in access to GPs for these groups are not reflected in the use of practice nurses in primary care. The degree of urbanisation is found to have a significant impact on practice nurse visits (joint significance p value = 0.0266) but not GP visits (p value = 0.7644), with people living in rural areas being more likely to see practice nurses compared with people living in suburban areas, all else equal. One explanation for this finding is that there are unobserved practice nurse supply or need factors that are correlated with rurality that cause more use in rural areas. However, this is conjecture and we recommend further research to investigate this issue, especially given the interest in the health and health care provided in rural communities (Asthana *et al.*, 2009). In the case of ethnicity, individuals in different ethnic groups were not more likely to visit a practice nurse, while Pakistani and those belonging to 'Other' ethnic groups have a higher probability of visiting a GP, all else equal. This might be consistent with previous evidence on patient satisfaction with skill mix in primary care that have found that *"[…] ethnic minorities want a 'traditional' GP-led service"* (Branson *et al.*, 2003). Previous research have also shown that members of non-white ethnic groups tend to consult the GP more than whites (Benzeval & Judge, 1994; 1996; Smaje & Le Grand, 1997; Alexander, 1999).

As expected, use of primary care services is positively correlated with the supply of services. Distance to general practice has a negative effect on the probability of visiting the practice nurse. GP supply is positively correlated with both types of contact. The supply of practice nurses in the area, measured by the number of practice nurses per 1,000 registered patients, was found to be non-significant in both equations. The most likely explanation for this is that since practice nurses are employed by GPs the numbers of GPs and practices nurses will be positively correlated, and this causes the effect of practice nurse supply to be non-significant conditional on GP supply.

In our analysis we have investigated and compared the effect of the need indicators on GP and practice nurse use, which led to some interesting results. Individuals with chronic ill health are significantly more likely to see the practice nurse, while the effect on GP visits is non-significant. Acute ill health increases the probability of both types of contacts but has a bigger effect on the probability of seeing the GP. In terms of specific longstanding illnesses treated by practice nurses and GPs, we found that while most of the conditions are positively related with GP visits, practice nurses play a significant role in a smaller range of conditions, especially for patients with endocrine and metabolic conditions, heart and circulatory problems and respiratory system conditions. Given that many of these illnesses are long-lasting or recurrent, this appears to reinforce the role of practice nurses in treating chronic ill health. Diseases of the nervous system, mental and psychosocial disorders do not increase the probability of seeing a practice nurse. These findings are consistent with previous research that has shown how practice nurses are increasingly responsible for the care of patients with chronic diseases, and how the practice nurse role is "least advanced" for patients with mental health problems (The Centre for Innovation in Primary Care, 2002).

The main strength of our analysis is the richness of our dataset. In particular, as well as having evidence on both practice nurse and GP visits, we have comprehensive information on morbidity and so can argue that it is less likely that the estimated effects of other variables in our models are due to their correlation with omitted morbidity variables. Also, by controlling for supply we reduce the risk of omitted variable bias from this source. We acknowledge a number of limitations with our analysis. First, the role of practice nurses is evolving over time; this may mean that the data used in this analysis from 2001 and 2002 does not necessarily reflect the current situation. However it does provide a baseline against which the role of practice nurses can be assessed in the future. Second, the HSE does not contain detailed information about the precise nature of practice nurse and GP visits and visits are measured crudely as binary variables for contacts in the previous two weeks. In particular, there is no information on the intensity and quality of care provided, nor on the type or specific skills of the nurse visited. Third, in order to fully measure horizontal inequity in primary care we would ideally have data on contacts with other professionals in primary care settings such as community health services, dieticians, etc. Fourth, the measures of morbidity are predominantly based on self-reported health that may be measured with error that is correlated with use (Sutton *et al.*, 1999). Finally, there may be reverse causality between use and morbidity (Sutton *et al*., 1999; Abásolo *et al*., 2001).

The analysis of horizontal inequity ignores the possibility that the estimated effect of the need variables on health care use may not be appropriate (i.e. vertical inequity factors). As illustrated in this chapter, horizontal equity is measured by comparing actual use with the average use received by individuals with the same needs across the whole population. This is similar to assuming that, ‘on average the system gets it right’ (van Doorslaer *et al.*, 2000), which has been criticised, especially when comparisons across different countries or time periods are made (Sutton, 2002). The assessment of the estimated effect of the need indicators can shed some light onto the issue of vertical equity (Gravelle *et al*., 2006). Some authors have argued that a ‘necessary but not sufficient’ test for vertical equity can be derived by testing whether the need indicators have a positive and significant effect on health care use (Abásolo *et al*., 2001). Although it seems plausible to assume that morbidity measures should have a positive effect on health services utilisation under the vertical equity principle, it may also be the case that no medical treatment is available or that a particular health service is not appropriate to treat specific conditions or types of patients. In our study, we found that individuals reporting very poor health did not have a greater probability of visiting a practice nurse, as neither did those with mental disorders or higher GHQ-12 scores. However, these individuals were significantly more likely to visit their GP. On the other hand, being permanently unable to work due to illness was not found to be correlated with GP use, but it significantly increased the probability of practice nurse services use.

Therefore, these results may suggest a substitution between the patients being treated by each type of health professional and does not necessarily implies inappropriate use for different needs. A more careful consideration of the expected effect of the morbidity estimates on health services is thus necessary in order to draw conclusions about vertical equity.

In summary, this chapter has illustrated the measurement and provided evidence of horizontal inequity in the use of primary care services. Our findings highlight the importance of including analyses of practice nurse visits as well as GP visits in the assessment of equity in primary care. We allow for the correlation between the utilisation of both types of services in the model estimation, but the equity indices were not found to be sensitive to this correlation. While the assessment of horizontal inequity in health care utilisation have extensively been analysed, considerations about vertical equity are rare in the literature. The following chapters of this thesis will focus on the overlooked issue of vertical equity in health care delivery.

CHAPTER 4

Methods to testing for and measuring vertical equity – a literature review

4.1. Introduction

This chapter reviews the literature that has empirically investigated vertical equity in the delivery of health care. The main aims of the review is to identify the empirical methods that have been applied to or proposed for exploring vertical equity, and to form an understanding on what it is known about vertical equity in health care delivery. The finding from this review will be used to inform the analyses undertaken in subsequent chapters of the thesis.

Little attention in the literature has been paid to vertical equity in health care. Exploring vertical equity requires making strong value judgements about the way health care consumption ought to vary amongst individuals with different levels of need (Gravelle *et al.*, 2006). Therefore, most empirical work only considers horizontal equity in health care utilisation, by examining the notion of 'equal treatment for equal need' (see e.g., Wagstaff *et al.*, 1991b; van Doorslaer & Wagstaff, 2000; van Doorslaer *et al.*, 2004; van Doorslaer *et al.*, 2006; Lu *et al.*, 2007; Bago d'Uva *et al.*, 2009). However, the need to move towards the measurement of vertical equity has been highlighted in the literature (e.g., Rice & Smith, 2001; Hauck *et al.*, 2002; Mooney, 2008), and therefore, a robust methodology is needed in order to makes this task possible. To our knowledge, no previous review has been undertaken that covers vertical equity in health care delivery, and so this chapter provides the first review on this topic. Our objective is to identify the papers that provide an interpretation, for empirical purposes, of vertical equity in the delivery of health care, by suggesting a methodology for either testing it or measuring it. The primary aims of this chapter are, therefore, first to provide a critical review of the methods employed in the literature to date to test for or measure vertical equity in the delivery of health care and second to identify which methods are best suited to measuring vertical inequity. The considered shortcomings of available studies are thus emphasised. Additionally, we also explore the empirical literature in vertical equity in other fields rather than health care delivery and assess the potential of adjusting the methods developed in other areas to measuring vertical equity in health care delivery.

The chapter is structured as follows; the methods section describes the review methods applied to identify and critically assess the relevant studies; the results section provides a summary and a critical appraisal of the papers identified; while the final section concludes and draws the main implications for further work.

4.2. Review Methods

4.2.1. Main search

This search was guided by the research question: How has vertical equity in the delivery of health care been explored in empirical investigations?

The term ‘delivery’ is used throughout the chapter to refer to either the distribution of the utilisation or access to health care services, or to the allocation of health care resources across individuals or areas.

The literature search was carried out using the electronic databases Scopus (http://www.scopus.com), Econlit (http://www.aeaweb.org/econlit/index.phpand) and IDEAS (http://ideas.repec.org). We used the following terms in the full text: (‘vertical equity’ or ‘vertical inequity’) and (‘delivery’ or ‘utilisation’ or ‘utilization’ or ‘use’ or ‘access’ or ‘resource allocation’). Titles and abstracts of all the articles identified were reviewed and relevant studies were obtained. Additionally, titles of the Ecuity project (http://www2.eur.nl/bmg/ecuity) publications were also reviewed using the same search terms. The Ecuity project is an international project including members from a number of European countries and the US, which has developed a set of methodologies to provide practical tools for the measurement and explanation of inequality and inequity in health and health care.

Table 4.1 summarises the search methods of this review. Papers were included if they explicitly considered vertical equity in the utilisation, access or allocation of health care or health care resources, and they report (or suggest a methodology for) an empirical investigation. The studies did not have to undertake the empirical analysis but at least describe a methodology for the analysis of vertical equity in order to consider the study to be relevant. However, papers covering vertical equity that did not provide an empirical analysis or did not propose a methodology were excluded. For instance those studies highlighting the importance of looking at vertical equity or that focused solely on defining the concept and framework for vertical equity were not included. The reason for that is that the focus of this review is to identify the methods being applied to test for or measure vertical equity in health care delivery, rather than considering the conceptual literature of vertical equity. Articles from all years, from any population group and from any area that were written in English, Spanish or Portuguese which met the above criteria were reviewed.

Table 4.1. Summary of search methods to identify relevant studies

Search terms	('vertical equity' OR 'vertical inequity') AND ('use' OR utilisation' OR 'utilization' or 'access' OR 'delivery' OR 'resource allocation')	
Inclusion/exclusion criteria	**Include**	**Exclude**
Field	Utilisation of, access to or resource allocation of health care	Other
Empirical versus conceptual analysis	Provide empirical analysis or proposed methodology	Conceptual literature
Geographical area	All	None
Population	All	None
Year	All	None
Language	English, Spanish, Portuguese	Other

This search terms identified 147 studies[10], of which 23 met the criteria. Two additional studies were identified by the search in key readings on equity in the delivery of health care. Therefore, a total of 25 studies were included in the literature review. The list of papers is provided in Appendix 4.1.

4.2.2. Supplementary search

The aim of the supplementary search was to identify the methodologies that have been developed to measure vertical equity in fields other than delivery of health care. The research question in this case is: How has vertical equity been explored in empirical analysis of other fields rather than health care delivery?

[10] The last search was conducted on 31/03/2011.

This search was carried out using the terms ‘vertical equity’ or ‘vertical inequity’ in the title, abstract or key words. The reason for restricting the search to the papers using the terms in title, key words and abstract only, is that for the purpose of the supplementary search only studies with main focus on vertical equity would be relevant. The same inclusion/exclusion criteria as in the main search were applied with the exception of the field of the papers, which was not restricted and all fields were considered. However, only key methodological papers that were found to provide the basis of the methods applied to a number of studies in the same field or that provided an improvement to the existing methodology were selected. The justification for this is that the aim is not to fully revise the extensive literature of vertical equity that is available in other fields, such as the finance system for instance, but to identify the methods that are employed which could then be adjusted for the measurement of vertical equity in health care delivery.

The search identified 172 studies, of which 7 were considered the most relevant papers and were included in the review. The papers are listed in Appendix 4.2.

4.2.3. Criteria for assessment

Gravelle *et al.*, 2006 emphasise some of the main challenges of empirical research in equity. They highlight the issues of the distinction between need and non-need variables; the omitted variable problem; and disentangling horizontal and vertical equity. We use these conditions as a vehicle for selecting the methodologies more capable of addressing these problems.

Separation between need and non-need variables would depend largely on values judgments. However, it is commonly accepted that measures of health status and morbidity ought to affect health care use, while especially in individual-level analyses with health and morbidity data, socioeconomic indicators are generally considered to be non-need indicators.

In the case that needs are not comprehensively measured, socioeconomic indicators may be picking up the effect of unobserved need factors. In that case the analysis would be affected by the omitted variable problem. Although the extent to which needs are captured depend largely on the availability of the data, we consider the potential of the methodology to account for needs comprehensively.

Gravelle *et al.*, 2006 pointed out that the exploration of vertical equity requires estimating the appropriate way in which health care consumption ought to vary for individuals with different levels of needs. Without the knowledge of the optimal effect of needs on health care delivery, conclusions about whether individuals with different needs are being appropriately treated cannot be drawn.

In addition, the authors recognise that separation between vertical and horizontal aspects is not straightforward. Gravelle *et al*., 2006 highlighted that both horizontal and vertical inequity would have distributional consequences for the population groups identified by the other; *"[a] negative correlation between morbidity and income, for example, means that pro-healthy vertical inequity will tend to benefit those on higher incomes. Conversely, pro-poor horizontal inequity will tend to mean that the sick have higher than expected levels of consumption"*. Therefore, separation between vertical and horizontal inequity aspects was considered to be one of the main challenges in equity analyses in health care.

Furthermore, measures of inequity that allow for the quantification of the extent of inequity and, therefore, comparisons across time and areas, are believed to provide an advantage over the methods only capable of identifying vertical inequity. The reason being that the measurement of inequity it is important insofar as provides the means of determining the magnitude of the problem and to monitor the progress of the policies designed to tackling these inequities.

4.3. Summary of the papers

4.3.1. Main search

The measurement methods of vertical equity employed to date in the literature do not only differ by the specific metrics or measures analysts have used in their studies; but also by the general approach and by the assumptions underpinning their analyses. Although the focus of all the identified studies is to identify the relationship between needs and health care delivery, the studies vary by the definition of need; by the dimension of inequity under analysis (i.e. whether they focused on the effect of the need indicator solely or whether they looked at the distributional consequences across other population groups); and by the test to assess whether the situation was or was not vertically equitable. According to the approach being used, papers were classified into eight categories and are summarised in Table 4.2.

In most of the papers, need is measured by health status, although socioeconomic status, ethnicity and an composite index of service and material use and health status have also been used as a proxy for needs. The aim of the majority of the studies was to find deviations of the vertical equity principle with respect to the need indicator; however some papers focussed on exploring vertical equity with respect to one social characteristic, such as gender or income. Finally, some of the papers included in the review do not to provide a measure of vertical equity but try to generate an allocation of resources that is more vertically equitable. Nevertheless, the implicit test for vertical equity is derived from these studies. The description of the specific metrics and techniques applied in the test or measurement of vertical equity in each of these studies are presented in Table 4.3. Appendix 4.3 shows a more detailed summary of all the papers included in the review.

Table 4.2. Approaches to testing for or measuring vertical equity in health care

Approach	Description	Measure of Needs
1	Test the association between SES and health care delivery	SES
2	Compare ranking of observations according to need and according to health care delivery	Health service use, material resource use and health status
3	Test the effect of health indicators on health care delivery after controlling for SES	Health status
4	Test the association between a non-need factor and health care delivery at different levels of health status	Health status
5	Test the association between health outcomes and health care delivery across a non-need factor	Health outcomes
6	Compare actual and target effect of the need indicators	Ethnicity; SES
7	Compute the health care gap function between target and actual health care delivery	Health status
8	Test and measure the difference between target health care delivery and need-expected health care delivery across SES	Health status

Note: SES = socioeconomic status

Table 4.3. Metrics identified in the literature to testing for and measuring vertical equity in the delivery of health care

Approach	Studies	Metric	Description
1	Alberts et al., 1997	Unadjusted odd ratio	Compute the odd ratios and regression coefficients of health care use for different SES groups
1	Browell et al., 2001	Ratio analysis	Compute the ratio of health care delivery for each income quintile group over a period of time
1	Zere et al., 2007	Concentration curves	The visual comparison of the concentration of need across SES and the concentration of health care delivery across SES
1	Voncina et al., 2007	Adjusted odd ratios	Compute adjusted odd ratio of health care use across SES groups
1	Baldani et al., 2009	Correlation coefficient	Measure the degree of association of SES indicators and health care delivery
2	Rocha et al., 2004	Coefficient of concordance	Measure the degree of concordance of the hierarchy of observations ranked by level of need and by health care delivery
3	Abásolo et al., 2001 Gravelle et al., 2006 Liu et al., 2002 Antioch et al., 2002 Matovu et al., 2009	Regression coefficient	Compute the effect of health indicators on health care delivery after controlling for non-need indicators
4	Raine, 2002 Raine et al., 2004	Interaction term	Compute the effect of the interaction of a need and a non-need indicator on health care delivery
5	Raine et al., 2002	Adjusted odd ratios	Compare the difference in severity at admission with the risk-adjusted odd ratios of mortality across gender groups
6	Mooney et al.	NA	Suggest asking the community to find the appropriate weights of the need elements
6	Sutton et al., 2000	NA	Suggest using the most responsive area to find the appropriate weight of the need indicators
6	McIntyre et al.	NA	Compares graphically the shares across areas of the allocation of health care resources under the actual allocation and under an allocation that incorporates a vertical equity adjustment
7	Laudicella et al., 2009	FGT poverty index	Suggest computing the poverty index of the gaps between target and actual health care delivery
8	Sutton, 2002	Concentration index	Compute the difference of the concentration of need-predicted health care delivery and target health care delivery with respect to SES

Note: SES = Socioeconomic status; NA = Not Applicable

Each of these approaches to testing for or measuring vertical equity in health care delivery is discussed below, summarising the assumptions behind, the variety of empirical methods applied and the main finding of the studies. A critical appraisal of each of the approaches is presented at the end of each subsection.

Approach 1 - The association of SES and health care delivery

This approach is based on the association between socioeconomic status and the delivery of health care. The assumption underpinning this approach is that individuals in lower socioeconomic groups are in higher needs and they should therefore receive more health care in order to meet the 'unequal treatment for unequal needs' vertical equity principle.

In a general framework, let's denote q_i as health care delivery and Y_i the increasing socioeconomic status for individual *i*. This approach is based on the relationship between q_i and Y_i such that the lower the socioeconomic status of the individuals, the higher the health care delivery they should receive,

$$q_i = \alpha + \delta Y_i + \varepsilon_i \qquad (4.1)$$

$$\frac{\partial q_i}{\partial Y_i} = \delta \prec 0$$

Five articles were found to test for vertical equity using this approach. Each article used a different metric to identify the relationship between SES and health care delivery.

Albert *et al.*, 1997 tested for vertical equity by looking at the odd ratios (and coefficients) of educational level on the probability (and volume) of health care consumption in Curacao, The Netherlands using bivariate analyses. They first looked at the correlation between education and health measures, and found that high education was positively associated with health. They then regressed a number of measures of utilisation against education and found that education increased the probability to consult a dentist and a physiotherapist and the volume of dentist visits, which they interpreted as evidence of vertical inequity. After controlling for differences in age, gender and health indicators, education continued, and in some cases more strongly, to affect health care use, which they concluded to provide evidence of *horizontal* inequity.

Brownell *et al.*, 2001, looked at the effects of the health reform undertaken in Winnipeg, Canada. They explored the effect of the reform, which involved the closure of almost 24% of hospital beds, on vertical equity by comparing the relative utilisation rates before and after the reform for each income quintile group. They considered lower socioeconomic groups to be the most vulnerable groups which ought to have higher access rates, as they had prior to the reform. By computing the ratio of utilisation for each income quintile group over the period under analysis (1991-1996), they found that all socioeconomic groups maintained their relative access levels, and concluded that bed closures did not erode the vertical equity which existed in the system.

Zere *et al.*, 2007, computed concentration curves of health status and health care utilisation across household economic status for three years of data in Malawi. They looked at the concentration of health care utilisation and the concentration of health status separately, with respect to household wealth. They showed that the burden of any of the diseases considered in the paper was concentrated among the poor. Their test for vertical equity involved looking at the concentration of health care with SES. Their finding suggested that health care use was either equally distributed or distributed in favour of the non-poor. The authors interpreted this as evidence of vertical inequity.

Voncina *et al.*, 2007 looked at vertical equity in preventive health care services in Croatia. They considered the unemployed to be in higher needs and tested for whether unemployment status increased the probability of using health care preventive services. In their analysis they stratified by whether individuals were healthy or suffer from cardiovascular or metabolic disease, and computed the odd ratios of being unemployed in both samples. However, the test for vertical equity carried out in this study simply looked at whether the unemployed, who under their view should be positively discriminated in the provision of health care, received more preventive interventions in each group. They argued to find evidence of vertical inequity.

In a more recent paper, Baldani *et al.*, 2009 argued to provide evidence of vertical equity in the provision of dental services in Paraná, Southern Brazil between 1998 and 2005. They computed the Spearman coefficients of correlation between measures of access, utilisation and financial resource with SES indicators. They found in most cases a negative association, which they interpreted as a redistributive or positive discrimination effect showing vertical equity. In addition, they computed the Friedman test for the comparison across years in the provision and use of health services, and the Mann-Whitney test for the analysis of the differences between the poorest and the richest quartiles. They found significant differences between the income quintile groups favouring the poor in the provision of dental health services in the period under analysis.

In the absence of good epidemiological data, area level analyses often rely on socioeconomic indicators as their measures of need (see e.g., Sutton *et al*., 2002; Morris *et al.*, 2007). However, in individual level studies and/or when information on health and morbidity are available the choice of SES as a measure of need is very contested. Although the correlation between SES and health is well documented, and in some of these papers they explore the association among these two factors, it does not imply that differences in SES would only be reflecting differences in needs. Therefore, the interpretation of the association of SES with health services use becomes ambiguous. Moreover, there may be medical needs over and above the SES of the individual which will not be picked up by this sort of analysis. These analyses are also not able to disentangle whether their findings provide evidence of vertical or horizontal inequity, as they cannot judge whether individuals who received different amounts of health care did so because they had different legitimate needs or because they had same needs but different SES. Even if socioeconomic indicators where an appropriate measure of relative needs, this analysis cannot conclude whether the differences in treatment received by those in lower SES was *appropriate* to meet their relative higher needs, neither would be able to measure the extent of vertical equity. Therefore, this approach is considered very limited for the analysis of vertical equity.

Approach 2 – Compare the ranking of observations according to needs and according to health care delivery

This method is based on the comparison of the hierarchy of observations when ranked according to a measure of needs with the hierarchy of observations when ranked according to the delivery of health care received.

Rocha *et al.*, 2004 proposed this methodology in the context of exploring the degree of equity in resource allocation of per capita health expenditure. They create a need index using a large number of indicators of medical service use, such as percentage of population receiving vaccines; material resource availability, such as number of beds; and health status measured by a healthy life years lost per 1,000 insurance holder of the leading 10 causes of death. The healthy life years lost was computed as a compound measure which considers the incidence rate per year of each of the 10 diseases, average age of each age group at onset of disease, average age at death; life expectancy; lethality rate, proportion and extent of disability, and average disability duration for each disease. They considered areas with lower service and material use, and higher number of life years lost to be in higher needs. They computed the hierarchy of areas by the index of needs, and the hierarchy of areas by the allocation of per capita health expenditure, and measured equity by the Kendall's coefficient of concordance between these two ranking variables. The study concluded that a low concordance was found between these variables, with for instance, out of the 17 areas, Nuevo León ranked third with respect to the need index, but concerning the expenditure it had the 12th position.

The main problem with this approach is that, although this paper provides a framework for testing if the delivery of health care is *ordinally* appropriate, it fails to account for whether the allocation would be *cardinally* appropriate, i.e. whether the size of the differences in per capita expenditure across areas is enough to account for their relative difference in needs; which is required to analyse vertical equity. Hence, the method proposed in this paper is not believed to provide an appropriate measurement of vertical equity.

Approach 3 - The association of health indicators with health care delivery

The method consists of the assessment of the effect of health indicators on health care consumption after controlling for a number of other non-need indicators. Non-need indicators are factors that ought not to affect health care consumption after controlling for the effect of the need indicators; in this case thus SES variables are considered to be non-need indicators. Therefore, following from Equation (4.1), let N_i denote the measure of ill health for individuals *i*,

$$q_i = \alpha + \delta Y_i + \beta N_i + \varepsilon_i \qquad (4.2)$$

This approach focuses on the effect of the need indicators, requiring that individuals with higher level of ill health receive higher level of health care,

$$\frac{\partial q_i}{\partial N_i} = \beta \succ 0$$

Four out of the five studies in this section have tried to incorporate some assessment of vertical equity by looking at the regression coefficients of the need variables included in their regression models used to test for horizontal inequity, which control for a number of demographic and socioeconomic factors. The remaining study looked at the allocation of health care resources across hospital and its relationship with health indicators.

Abásolo *et al.*, 2001, defined the test of vertical equity in utilisation and access to GP services in Spain. They tested for vertical equity in *utilisation* by looking at the effect of the health indicators and the interactions between acute and longer-term health indicators on the probit model for the probability of consulting a GP for females and males separately. They also suggested testing for vertical equity in *access* to GP visits by including interaction between determinants of access (travel time) and need variables, although this is not undertaken in their analysis. They found that overall GP utilisation in Spain was consistent with a principle of vertical equity as those reporting acute ill health, those reporting worse than 'very good' health, and some chronic conditions had a significantly higher probability of seeing a GP. For females, an exception to this is found relating to the interactions between acute and longer-term health indicators.

Liu *et al.*, 2002, computed the odd ratios of outpatient care, inpatient care, emergency and diagnosis services for individuals with chronic illnesses in Zhenjiang city, China after controlling for a number of demographic and socioeconomic indicators. They also calculated the change in the effect of the chronic illness variable before and after a health reform. They found that chronic disease status was the most significant predictor with individuals chronically ill being from two to four times more likely to have health care use. After the reform, individuals with chronic illnesses were borderline significantly more likely to use outpatient visits, while they were less likely to have an emergency visit.

Gravelle *et al.*, 2006, looked at the coefficient of health indicators in the probability of having a GP consultation, outpatient visit, day case treatment and inpatient treatment in the UK. They found that worse levels of self-reported health were associated with greater utilisation for all services, and that having a limiting longstanding illness increased the probability for inpatient and outpatient treatment; however they found that the test for vertical equity was not passed for a measure of psychosocial disorders for three types of health care, and the presence of some longstanding illnesses significantly reduced the probability of inpatient stays.

Matovu *et al.*, 2009 considered under-five to be in greater need of insecticide-treated nets to prevent malaria due to their lower immunity. In their study, they regressed the probability of using a bed net using logit models. They found that under-five were more likely to use a net after controlling for other socio-demographic characteristics, but the differences were relatively small which they argued may imply that the situation was still likely to be vertically inequitable.

In the context of funding arrangements in Australia, Antioch and Walsh, 2002 proposed a risk-adjusted capitation funding model which includes a 'complexity' component reflecting differences in risks. They run a cost per patient multivariate model and found a significant and positive effect of the patient casemix complexity scores. The authors argued this model achieve greater vertical equity through differential payment related to differential need.

Looking at the regression coefficient of the need variables after controlling for non-needs indicators allow to disentangle the effect of the need and non-need variables on health care use, and separate the horizontal and vertical aspects of inequity. The assumption to testing for vertical equity is that morbidity measures should have a positive effect on health services utilisation, while horizontal equity is tested by whether the non-need variables have an impact on health care delivery. However, as exposed in Chapter 3, although it seems plausible to assume that morbidity measures should have a positive effect on health services utilisation under the vertical equity principle, it may also be the case that no medical treatment is available or that a particular health service is not appropriate to treat specific conditions. Therefore, a more careful consideration of the expected effect of morbidity estimates on determined health services is necessary in order to draw conclusions about vertical equity. Furthermore, as most of these studies recognised, the vertical equity test cannot discern whether the degree of increased utilisation by sick individuals adequately meet their relative need as compared with the healthy. More specifically, Abásolo *et al.*, 2001 argued that '*[...] a further requirement is that the size of these coefficients are significant in policy terms. That is, they should exceed the threshold P_u that corresponds to policy-makers' notion of how much greater use 'needy' individuals should make of GP services.*' In other words, this approach does not set a target for the effect of the need variables that could then be compared with the actual effect. Therefore, without this notion of the appropriate effect of the need variables on health care utilisation, a full test for vertical equity cannot be derived; neither the extent of vertical inequity could be measured.

Approach 4 - The effect of SES on health care use at different levels of needs

Other papers that have looked at vertical equity have explored whether non-need variables affect health care consumption at different levels of health by interacting need and non-need variables. This is equivalent to including the interaction between the need and the SES variable in Equation (4.2) to give:

$$q_i = \alpha + \delta Y_i + \beta N_i + \sigma N_i * Y_i + \varepsilon_i \quad (4.3)$$

and then test for $\sigma = 0$; therefore, the requirement for vertical equity is that the effect of health status on health care delivery does not vary across different non-need groups. The reason is that differences in health care utilisation across sick and healthy individuals cannot be regarded as appropriate as long as they are affected by the differences in their non-need characteristics, such as income.

Raine, 2002, and Raine *et al.*, 2004 proposed to use this method. The idea is that when no differences in utilisation are found with respect to a social characteristic after adjusting for needs it is often said to reflect fair health care use with respect to that characteristic; but this *assumes* that at every level of need the difference in health service use across that social characteristic is the same. They suggest testing that assumption by examining interactions between the non-need variable and a need variable. Raine *et al.*, 2004 focus on the effect of gender (which it is assumed in their analysis to be a non-need variable) on patient referral to cardiac rehabilitation for different levels of severity. They included a number of interactions between severity levels and gender, and found that males with hypertension were nearly twice as likely to undergo rehabilitation compared with females with hypertension.

Interacting need and non-need variables has also been proposed in the literature as a means of testing for *horizontal* inequity. Wagstaff and van Doorslaer, 2000 suggested looking at the interaction between needs indicators and a non-need variable (in that case income) to test for horizontal inequity, arguing that if ill individuals when they are rich receive more health care than the poor, the principle of ‘equal treatment for equal needs’ is not met. As Gravelle *et al.*, 2006 have pointed out finding that morbidity coefficients vary across income groups indicates that patterns of inequity cannot be separated into horizontal and vertical aspects. Hence, this approach cannot be used as a direct test for vertical or horizontal equity. Moreover, using this approach, inequity is only identified with respect to the social characteristic that is interacted with the need variable, and therefore it does only pick up part of the extent to which individuals in unequal needs do not receive appropriately unequal treatment (i.e. income may not affect how much health care sicker individuals receive as compared with relatively healthier individuals, but the greater utilisation made by sicker individuals may remain inappropriate for their given higher needs).

Approach 5 - Health outcomes derived from unequal treatment across non-need groups

This method focuses on the association between health outcomes and treatment across different groups. The idea behind this approach is that if individuals are unequally treated with respect to one social characteristic but this is accompanied by no differences in their final health outcomes, then the unequal treatment was justified by their unequal needs and this meets the vertical equity principle. In the general framework, where H_i stand for the health outcome of individual *i*,

$$q_i = \alpha_0 + \delta_0 Y_i + \varepsilon_i \quad (4.4)$$

$$H_i = \alpha_1 + \delta_1 Y_i + \varepsilon_i \quad (4.5)$$

the delivery of health care would be believed to be vertically equitable if $\delta_0 \neq 0$ in Equation (4.4), but $\delta_1 = 0$ in Equation (4.5); i.e., the difference in use across SES groups do not translate in differences in health outcomes across these groups. Similarly, if $\delta_0 = 0$ in Equation (4.4.), but $\delta_1 \neq 0$ in Equation (4.5) it would indicate that equal treatment across SES groups was not appropriate, as individuals ended up with different health outcomes.

Raine *et al.*, 2002 looked at the effect of patient gender on admission to intensive care unit (ICU). They compared the gender differences in severity at admission to ICU (by looking at the t-test, Mann-Whitney U test or Pearson χ^2 test for age, medical history and risk scores) with the gender difference in adjusted mortality risk during hospital stay (by computing the risk-adjusted odd ratios). The assumption is that if, for instance, males admissions had a lower severity than females admissions, and this suggests that the disease severity admission criteria for females was more stringent than for males. However, if this unequal treatment was accompanied by no gender differences in risk adjusted mortality, it implies that vertical equity was achieved by providing unequal treatment to unequal needs. They found that for myocardial infarction, males had lower severity at admission than females, and were also less likely to die which suggests vertical inequity. In addition, for other conditions such as brain injury, pneumonia, or ventricular failure, there were no differences in severity by sex but one gender had a higher mortality risk, which showed vertical inequity.

The main limitation of this paper to assess whether different treatment was being provided across gender groups is that there is not data on patients *not* admitted to ICU, and therefore it is difficult to conclude that a more stringent criterion was applied to one gender by simply looking at the differences in severity of those who were admitted. In terms of the approach, the main limitation is the strong assumption that differences in health outcomes are simply a result of differences in the treatment received. There may be a wide range of reasons why individuals receiving different treatment end up having same health outcomes which do not relate to differences in their treatment but rather to inefficiencies in the provision of health care or to non-care factors, such as social determinants of health. In addition and similarly to the previous method, this analysis only focus on the deviation of the vertical equity principle with respect to the social characteristic of interest and would not therefore be able to fully capture vertical inequity.

Approach 6 – Comparing the actual effect of need indicators on use with the target effect of need indicators

This approach focuses on one part of the measurement of vertical equity which consists on finding the appropriate weights of the need indicators in order to allocate resources under the vertical equity principle. The papers included in this section did not attempt to derive a full test for vertical equity but the test can be inferred from the methodology used. The idea is to find the appropriate weights of the need indicators such that individuals with unequal needs receive appropriately unequal treatment. Once the appropriate weights have been derived, they can be compared with the actual weights in order to assess whether the situation was vertically equitable. Therefore, this test can be summarised by whether the estimated effect of the need indicators equal the target effect of the need indicators such as:

$\beta = \beta^*$, where β^* stands for the target effect or weight of the need element.

With respect to the general approach, this methodology provides the basis for the *test* of vertical inequity; however it is not capable of *measuring* the extent of vertical equity, and therefore prevents from the quantification of inequity across time or areas and does not assist in monitoring improvements towards reducing vertical inequity.

With regards to the identification of the appropriate effect of the need elements, we summarise the specific approaches proposed in the papers identified. Mooney, 1996; 2000; Mooney and Stephen, 1997; Mooney *et al.*, 2002; Mooney and Henry 2004 emphasise the importance of looking at vertical equity, especially in countries where there are specific population groups having very different health status and health care needs than the average population, with especial emphasis on Aborigines in Australia when setting funding formulae. They suggested applying a weighting higher than one to the health gains of individuals who are considered worse off as compared with some average. The idea is that by basing the allocation only on differences in morbidity, *"[…] groups in greater needs will, ceteris paribus, get more resources allocated to them. […] but it will not be the case that priority will be given to health gains to one group rather than another".* The authors argue that society might want to give preference, on vertical equity grounds, for health gains of groups which are in average in poor health, such as the poor, Aborigines, etc. They suggest asking the community about the weightings that ought to be applied in the funding formula for the health gains of different groups, which for instance in Mooney, 2000 were found to be above one, and sometimes around 3 times higher, for example for indigenous population.

McIntyre and Gilson, 2000; 2002; McIntyre *et al.*, 2002 draw extensively on the work of Mooney and colleagues. In these papers, the authors explored the distributive implication of changing the weights of the needs elements of the funding formula in order to ensure greater vertical equity.

McIntyre and Gilson, 2000 explored the implications of two scenarios in the allocation of resources across areas in South Africa: i) switching the weighting of two components: the 'economic activity' component which favours the most advantaged areas (the element received a weighting of 8% in the original formula), and the 'backlogs' component which increase allocation to areas with the gravest human development backlogs but only received 3% weighting in the original formula; and ii) removing the 'economic activity' component and giving the backlog component a weighting of 11%. They concluded that doing these changes would enhance the redistributive impact of the formula achieving greater vertical equity. To show this they presented graphically the percentage shares of each area under each scenario and judge whether the areas which gain the most were among those most disadvantaged with regard to a number of deprivation measures.

McIntyre *et al.*, 2002 derived a deprivation index that was included as one component of the resource allocation formula with different weightings attached to it. The deprivation index was derived using principal component analysis and included a number of socioeconomic indicators such as rurality, schooling, access to piped water, etc. They computed, and compared graphically, the allocation of resources and found that distributive effects were negligible with the 8% weighting of the 'economic activity' component used in the current formula; but when the weighting was changed, very deprived provinces saw quite dramatic potential budget increases.

McIntyre and Gilson, 2002 compared the actual allocations across provinces for five financial years with a budgetary allocation that was adjusted to remove the population already covered by insurance. The authors provided a graphical representation of the distance of allocations in each province to this 'equitable' allocation across time and concluded that the resource re-allocation provided a useful starting point for promoting vertical equity in early years as those provinces which were the main beneficiaries of resources redistribution were those with some of the worst health status indicators. However, this pattern was reversed in subsequent years.

Sutton and Lock, 2000, explored the implications of including a vertical equity objective in developing a resource allocation formula across Health Boards in Scotland. They challenged the current approach of applying the national average relationship between need characteristics and health care use, and suggested using the relationship of the most responsive area (the board that allocates proportionally more resources to individuals in higher needs) in order to derive the relative need index. In order to identify the most responsive board, they computed the Kakwani index (see details below) of health care with respect to needs for every board. Furthermore, the authors argued that vertical equity would be achieved when the differential level of health care resources received by high- and low-need small areas nationally is the same as in the most progressive area. In order to do that, it is necessary to address for the within-area allocation of resources. Therefore, the vertical equity adjustment need to account for the fact that, for instance, in a situation with two areas with the same population and the same need index, if the areas are given the same resources but area A allocates

80% of their resources to needy individuals within the board, while area B allocates only 60% to needy individuals within the area, this implies that on average only 70% of the national resources will go to needy individuals. If we believe that nationally 80% of resources ought to be targeted to needy groups (as in the most progressive area), we need to further adjust for this. The proposed adjustment is based on the assumption that the allocation of resources across need groups within an area will not be affected by the resources available in that area. This may not necessarily be the case if, as the authors recognised, as the resources availability in the area increases, need groups ensure the fair share more appropriately. Even in the case that areas continue to allocate resources inequitably within an area, it would be contested to argue that more resources ought to be allocated to these areas in order to increases the national average of propensity to spend on needs. Policy action in terms of monitoring and ensuring a better allocation of resources within areas would provide a better solution to address this problem. This is the current practice in the resource allocations formula design which does not focus on the within area allocation but on providing an allocation across areas that meet the equity criterion.

In terms of finding the appropriate effect of the need elements, the approaches suggested in these studies are not very convincing. Mooney and colleagues' approach based on community preferences, implies that the additional weight given to particular groups of individuals is not necessary related to their additional needs, but related to the view of the community about who, and to what extent, ought to be given preference in terms of health care delivery. Therefore, this approach could become problematic if, as Peacock and Segal, 2000 already pointed out, the community's view turns out to be contradictory to the policy makers' notion of fairness on health care. In addition, these views would not necessarily be based on expert knowledge about what it is required in terms of health care resources or health care services to improve the health of particular groups under consideration. The rather arbitrary way in which McIntyre and colleagues changed the weighting of the elements in the resource allocation formula show the difficulties that are likely to be encountered in finding the appropriate weights of the need elements. Sutton and Lock, 2000 used a more explicit way by using that of the area which allocates more resources to those in higher needs. However, this has also been considered arbitrary by others (Hauck *et al.*, 2002).

Approach 7 – Health care gap between actual and target health care

This method is based on an application of the contribution from the literature on poverty and deprivation to the measurement of inequity in the delivery of health care. The approach has been proposed for the measurement of horizontal inequity by Laudicella *et al.*, 2009. However, the authors recognised that it could be adapted to account for both horizontal and vertical equity. The general approach is to measure inequity as the distribution of health care gaps (HCG) defined as the distance between the target health care delivery and the actual health care delivery. They suggest the target health care to be exogenously set by policy makers as the minimum amount of health care resources that individuals or communities should receive given their need. The vector of HCGs is given by:

$$x_i = \max(q_i^* - q_i;0) \tag{4.6}$$

where, q_i^* is the target health care use; q_i is the actual health care use; the vector returns a zero value when individuals have equal or higher delivery than targeted. Laudicella *et al.*, 2009 use the FGT (Foster, Greer and Thorbecke) (Foster *et al.*, 1984) poverty indices that can be defined as a function of the HCGs,

$$\Delta_\alpha^{FGT}(x) = \int_0^\xi x^\alpha dF(x) \tag{4.7}$$

where α is a parameter that defines the social preference for the distribution of inequity among the individuals deprived in healthcare, i.e. the inequality aversion. If α =1, the concern is only about the average HCG of the population, if α > 1 ensures that an equalising transfer of healthcare from a deprived person to anyone who is more deprived decreases the inequality index; when α → ∞ the measure depends only on the most deprived individual (Rawlsian measure).

The main limitation of this approach for the assessment of vertical inequity is that the methods would not be capable of disentangling horizontal and vertical inequity aspects, as the difference between the target utilisation and the actual utilisation for health care would be affected by deviations from both the vertical and the horizontal inequity principles. Moreover, an additional disadvantage of this measure is that only captures health care inequity among individuals receiving less than targeted health care. It would be necessary to reverse the focus and consider the other part of the distribution to assess inequity overall in the system; but it is not possible to derive a measure that considers both parts together.

Approach 8 - Measuring the difference between target and need-expected health care delivery across SES

This approach applies the methods now widely used to measure horizontal inequity by the means of the concentration indices. It focuses on estimating the target effect of the need variables in health care use, and then measuring the difference between the target and the need-predicted allocation of health care delivery with respect to SES. In the general framework, let denote $\hat{q}_i$ to the predicted values of health care delivery from Equation (4.2) based only on the estimated effect of the need variables; and q_i^* the predicted values of health care delivery based on the target effect of the need variables,

$$\hat{q}_i = \hat{\alpha} + \hat{\delta}\,\overline{Y}_i + \hat{\beta}\,N_i \qquad (4.8)$$

$$q_i^* = \alpha^* + \hat{\delta}\,\overline{Y}_i + \beta^* N_i \qquad (4.9)$$

where in both equations, SES is set equal to the mean value $\overline{Y}_i$ in order to neutralise the effect of the non-need variables in the prediction. Equation (4.8) provides the need-expected (also referred to as need-predicted) allocation of health care; while Equation (4.9) provides the target allocation of health care based on the optimal effect of the need variables and the intercept; α^*, β^*. Therefore, this approach compares the allocation of health care based on the average effect of the need variables recovered from the utilisation equation with the allocation based on the optimal effect of the need variables. The method implies computing the concentration index (CI) of the need-predicted and target allocation of health care with respect to SES. The estimate of vertical inequity is the difference between the two. As shown in previous chapters, and following Wagstaff, 2002 the formula for the CI of socioeconomic inequality can be written as follows:

$$CI = 1 - (2 * (1 - R_i)) \sum_{i=1}^{n} \frac{q_i}{n\mu} \qquad (4.10)$$

where, *n* is the sample size; q_i is the health care utilisation measure; *μ* is the average health care use and $R_i = \frac{i}{n}$ is the fractional rank in the income distribution of the *i*th person, with *i* =1 for the poorest and *i* = *n* for the richest. Therefore, the CI is one minus the weighted sum of the share of the health care variable of each observation, where the weight is given by the position of the individual in the SES distribution of that population. The concentration index provides a summary measure of the magnitude of socioeconomic-related inequality in a health variable of interest, and by comparing a set of indices one can derive a clearer ranking when trying to compare inequality across a number of countries, regions or time periods. More details about this methodology will be provided in the following chapter.

Vertical equity is then measured as the difference between the CI of the need-predicted health care allocation and the CI of the target allocation,

$$VI = CI_{\hat{q}_i} - CI_{q_i^*} \tag{4.11}$$

Sutton, 2002 proposed this methodology to measure socioeconomic-related vertical equity. Using the methods proposed by the author, one needs to define the target effect of the need variables on health care consumption. The target allocation of health care was created imposing a strictly positive relationship between levels of morbidity and utilisation found at low level of need to the whole distribution of morbidity. He found pro-rich estimate of vertical inequity, i.e. the divergence between need-expected allocation of health care and target allocation of health care falls disproportionally on the poor, but this was not statistically significantly different from zero.

This approach is the most comprehensive applied to date for the measurement of vertical equity. The method controls for non-need indicators in order to appropriately separate the effect of need factors; it provides the comparison between the actual and the target effect of the need variables; and, in particular, it allows for the measurement of vertical inequity by looking at the distributional consequences across the income distribution. However, the focus of this approach is on the measurement of socioeconomic-related vertical equity, which although of interest, may be only part of the vertical inequity which is present in a system. The reason being that vertical inequity arises when individuals with unequal needs do not receive appropriately unequal treatment, and this definition does not rely on the inequity being identified with respect to the socioeconomic dimension solely. This approach appears to measure what Gravelle *et al.*, 2006 identified as the consequences of vertical equity for the groups identified by horizontal inequity, i.e. across the socioeconomic distribution. Further work to extend this methodology to ensure that the consequences of vertical inequity across the full need distribution are accounted will be undertaken in subsequent chapters of this thesis.

4.3.2. Supplementary search

The aim of this supplementary search is to explore whether the methods currently used to measure vertical equity in other fields provide a more appropriate methodology that could be adjusted to assess vertical equity in health care delivery. The papers identified in the search were classified into different fields and those covering or revising the methodology applied in their area for the measurement of vertical equity were selected. As state above, the focus was not to fully review this extensive literature, but to identify key papers that summarise the methodology developed in these fields. For this purpose, seven papers covering five different areas were selected and are listed in Appendix 4.3. Table 4.4 summarises the main characteristics of the methods applied in the five identified fields. The areas are: vertical equity in the finance system (where we focus on its application to the health care sector finance); vertical equity in poverty alleviation programmes; vertical equity in education funding; vertical equity in the transport sector; and vertical equity in aid allocation.

This section briefly summarises the methodology for each of these areas. The next step for appraising the methods applied in the reviewed fields is to assess how they could be applied in our framework of interest, i.e. for the measurement of vertical equity in the delivery of health care. Measuring vertical equity in the delivery of care implies exploring whether the distribution of one specific variable, in our case, health services or health resources, is distributed according to the optimal effect of a relevant characteristic, which in our context are needs. We then consider whether the potentially applicable measures would provide any advantage over the methods employed in health care delivery.

Vertical equity in health care finance

Wagstaff and van Doorslaer, 2000 cover the literature on health care financing and explain the methodology applied in empirical studies. Vertical equity in health care financing has focussed on the issue of how far health care is financed according to ability to pay. It is measured using the Kakwani's progressivity index which is the most widely used measure in the tax and health care finance literature, and it is defined as the difference between the concentration index of payments with respect to income, and the Gini coefficient for pre-payment income.

Table 4.4. Metrics identified in the literature to testing for or measuring vertical equity in other fields

Field	Metric	Description
Finance of health care	Kakwani index	Measure the difference between the concentration of payments with respect to prepayment income and the Gini coefficient of prepayment income
	Gini index	The difference between pre-payment Gini index and post-payment Gini index when individuals with the same pre-payment income are given their mean post-payment income
Poverty alleviation programmes	FGT poverty index	Compared the cost of inequality before the policy (given by the inequality aversion parameter) with the cost of inequality after the policy when individuals with same pre-policy income are given the same post-policy poverty gap
School funding	Weighted dispersion index	Observations are weighted by the inverse of a need characteristic and variations in per pupil revenues are compared before and after the weighting is applied
	Ratio of coefficients	The ratio of the estimated coefficient of need indicator to the optimal coefficient of need indicator multiplied by 100.
Transport sector	Surplus loss	Measure the effect of the change in costs and time savings for different income groups after the programme
	Gini coefficient	Compare the distribution of income before and after the programme is implemented
Aid allocation	McGillivray index	Weight the aid allocation given to recipients by the GNP per capita of recipient countries

Note: GNP = Gross National Product

$$\Pi_k = CI_{payments_i} - G_{pre-income} \tag{4.12}$$

where the CI is defined as in Equation (4.10) but now q_i stand for health care payments and *Ri* is the fractional rank in the pre-payment income distribution of the *i*th person.

The Gini coefficient is analogous to this index when q_i stand for the pre-payment income. The estimate equals zero if payments as a proportion of income is constant across the income distribution; if the payments as a proportion of income increase with income, the index is positive, and the finance source is considered to be vertically equitable or progressive.

The Kakwani index is applied in the health care finance literature to measure how far health care is financed according to ability to pay. In terms of the delivery of health care, the same index could be applied to measure how far health care is distributed according to needs, by applying the same formula that in Equation (4.12) such as,

$$\Pi_k = CI_{q_i}^{N_i} - G_{N_i} \tag{4.13}$$

where the Kakwani index is measured as the difference between the CI of health care delivery with respect to the variable denoting needs, minus the Gini coefficient of the need variable. If health care use as a proportion of need increases with needs the index will be positive denoting vertical equity. However, this measure can only discern whether the health care delivery system is 'progressive', which we can call 'responsive' in this setting, in terms of whether the system allocates more resources to individuals in higher needs. We would not be capable of assessing whether the system is 'responsive enough' or whether it 'overmeets' the needs of the population it serves. Therefore it does not provide an improvement with respect to the measures already developed in the delivery of health care.

In addition to this measure, and in the context of analysing the redistribution effect of the financing system, Aronson *et al.*, 1994 have demonstrated that the redistribution effect (RE), as measured by the change in the Gini coefficient before and after payments, can be decomposed into vertical redistribution (V), horizontal inequity (H) and degree of re-ranking (R). In order to make this decomposition one must identify individuals with the same pre-payment income who will be defined as 'equals' and grouped accordingly. The Gini index of post-payment income can then be decomposed into between-group and within-group inequality plus a re-ranking component due to households move from pre-payment to post-payment income distributions. The formula is given by,

$$RE = G^{X} - G^{X-P} = V - H - R =$$

$$= \left[G^{X} - G_0^{X-P}\right] - \sum_j \alpha_j G_j^{X-P} - R \qquad (4.14)$$

where G^{X} and G^{X-P} are the pre-payment and post-payments Gini coefficients, respectively. Vertical equity is measured as the difference between the pre-payment Gini index and the post-payment Gini index if there is horizontal equity in payments ($G_0{}^{X-P}$). This term is computed by grouping individuals with the same pre-payment income and giving everyone in the same group the mean post-payment income of the group. Horizontal inequity is measured as the weighting sum of the Gini coefficients of each income group *j* given by $G_j{}^{X-P}$, where the weights α_j are calculated by the product of the group population share and its post-payment income share.

If we were to analyse the redistribution of health after a health care delivery policy has been implemented, one could applied the methods developed by Aronson *et al.*, 1994 and decompose the redistribution effect into vertical, horizontal and re-ranking factors. In this case we would be interested in the redistribution of health in a population as measured by the difference in the Gini index of health before and after the policy. We would need to group individuals according their health level prior to the policy and then measure vertical equity as the difference in the pre-policy Gini index of health and the post-policy Gini index that gives everyone in the same pre-policy health group the average post-policy health level. Horizontal inequity would be measured as the weighted sum of the Gini indices for each post-policy health group, where the weight is given by the product of their population share and their health share. The re-ranking variable denotes the move of individuals in the health distribution after the policy is implemented.

This approach would be helpful for measuring the vertical redistribution of health after a policy is implemented, but it would not be capable of assessing the vertical equity of the allocation of health care for a given population at a particular time, and therefore its applicability is very limited. Even in the context of measuring the effect before and after a health care policy, the main problem with this approach is to assess the extent to which a health care policy contributes to the observed redistribution of health, as population health and its distribution is affected by a series of other factors.

Vertical equity in poverty alleviation programmes

Bibi and Duclos, 2005; 2007 provides the methodology for the measurement of vertical and horizontal equity in poverty alleviation programs. The focus is to measure equity by the changes in the poverty indices that emerge after one program is implemented. Vertical equity in this context searches for a reduction of the welfare gaps that separate unequal individuals. The measurement is based on the FGT poverty indices already discussed.

With regards to the applicability of this approach in the context of vertical equity in health care delivery, and similarly to the redistribution effect after payments, this approach is very limited as it focuses on the effect of a policy and assesses its vertical effect on the distribution of the population rather than exploring whether a situation is vertically equitable at a particular time. The use of the poverty gap literature for the measurement of the vertical equity for a given allocation of health care has been exposed above and their limitations have been highlighted.

Vertical equity in the allocation of school funding

Toutkoushian and Michael, 2007 provide a review of the methods used to test for vertical equity in school funding. These methods are all based on the identification of the relationship between specific characteristics and per pupil revenues, similarly to those already discussed in the literature on vertical equity in health care delivery (i.e. correlations, ratio analysis, regression coefficient, etc.). Two new measures are identified in this paper; the weighted dispersion measure, and the ratio of the estimated coefficient to the dollar amounts prescribed by the state’s foundation program (i.e. the optimal coefficient).

The weighted dispersion measure consists on weighting the per pupil revenue variable by the inverse of a given characteristic considered to measure differences in needs, which would remove the effect of that characteristic from per pupil revenues. The estimated variation of per pupil revenues is computed by using standard measures such as the range, variance, coefficient of variation, etc. before and after the weighting is applied, and both measures are compared. Reductions in variation after applying the weighting to per pupil revenues are interpreted as improvement of vertical equity. The weighted dispersion index could be applied to the measurement of equity in health care allocation by measuring the dispersion or variation of health care resources before and after the adjustment for the need indicator. However, this measure computes how much variation is left after controlling for differences in the needs of the individuals, which in fact provides an estimate of horizontal rather than vertical equity. Therefore, this measure does not provide an improvement with relation to the methods applied in the delivery of health care.

The authors of this paper also proposed a new measure of vertical equity when the appropriate weights of the factors considered relevant are assigned by the state and denoted β^*. Then, the vertical inequity is measured as the ratio of the estimated coefficient to the optimal weight of the vertical equity factor.

$$\hat{q}_i = \hat{\alpha} + \hat{\delta}\, Y_i + \hat{\beta}\, N_i \tag{4.15}$$

$$VI = \frac{\hat{\beta}}{\beta^*} * 100\%$$

Where $\hat{\beta}$ is the estimated effect of the relevant characteristics that is then compared with the optimal weight; vertical equity is achieved when VI = 100%.

Following Equation (4.15) we could measure vertical equity by the ratio of the estimated effect of the need variables on health care delivery to the optimal coefficient of need on health care delivery. This approach requires estimating the target effect of the need variables which reflect the relationship between the needs indicators and health care such that there is on average appropriately unequal treatment for people with unequal needs. The paper does not provide a methodology for estimating the target effect of the need variables rather than suggesting using the dollar amounts prescribed by the state's foundation program in the setting of per pupil revenues, when they are available. In the context of the delivery of health care this will require the policy makers' or medical experts' notion about how much the need characteristic ought to increase the resource allocation or the medical attention received by the individual for a given budget. If that term was available the ratio proposed in this paper would allow us to summarise in one measure how far the estimated coefficient is from this optimal effect and comparing it over time or across different settings, which provides an extension to Approach 6 identified in the delivery of health care. However, as compared with other summary measures of inequity such as the concentration index as used in Sutton, 2002, this ratio does not allow measuring the distributive effects of the difference between the estimated and target allocation across the whole distribution, focusing only on what happen on average in a population.

Vertical equity in transport economics

Vertical equity in pricing changes in the transport sector is concerned with the effect of the programme in the most disadvantaged groups, usually related to those in the lower income groups. The methods used in the literature to explore this issue are to compare the surplus loss (Raux & Souche, 2004) of different income groups after a policy is implemented; or to compute the Gini coefficient (Karlstrom & Franklin, 2009) before and after the implementation of the policy (similarly to the methods used to explore the redistributive effect of payments in the finance system but interpreting the full redistributive effect as vertical equity). In terms of the surplus loss approach, changes in surplus are defined as,

$$\Delta S_k = \Delta c' + VT_k \Delta t' \qquad (4.16)$$

Where $\Delta c'$ is the change in the cost generated by the programme, VT is the average value of time for category *k*, and $\Delta t'$ is the change in travel time. For every category of individuals *k*, ΔS_k is the change in the surplus. An assessment of whether individuals from the poorest economic groups are the ones suffering the highest losses would indicate vertical inequity.

This approach does not in fact provide a summary measure of the vertical equity but it simply suggests comparing the surplus losses of the different income groups to assess if a transport sector policy was benefiting the most advantages groups rather than the most disadvantages groups. In the context of health care delivery this would imply comparing whether the health of the worse off in terms of health status increased more than the health of the better off after a health care policy is implemented. Therefore, this approach is only applicable for the exploration of a vertical effect after policy action in health care have been undertaken rather than measuring vertical equity of a particular allocation, which, as already discussed, limits the applicability of the approach. Moreover, this is in fact more appropriately measured by the comparison of the Gini coefficients before and after the policy as suggested by Karlstrom and Franklin, 2009, but applying the decomposition proposed by Aronson *et al.*, 1994 to partition the vertical and horizontal equities effects. Notwithstanding its appeal, this methodology accounts for a series of limitations as we discussed above.

Vertical equity in aid allocation

In the context of aid allocation equity indices, vertical equity is satisfied if a reallocation of aid from a richer recipient to a poorer one raises the value of the index of equity. Following Rao, 1994, considering a marginal reallocation of aid from recipient *n* to recipient *m*, then the reallocation will increase the value of the index, so long as recipient *n* is richer than recipient *m*.

There are a number of indices used in the aid allocation literature that satisfied this property such as the McGillivray index, and the extensions to it introduced by Rao, 1994. The McGillivray index is given by:

$$M_j = \sum_i \left[\frac{y_{uj} - y_{ij}}{y_{uj} - y_{\ell j}}\right] * \left[\frac{a_{ij}}{\sum_i a_{ij}}\right] \qquad (4.17)$$

Where, *i, j* are indexes of recipient and donor countries respectively; *y* is realized GNP per capita; a_{ij} is per capita aid received by *i* from *j*. The term within the first square brackets denotes the weight assigned to the *ith* recipient. The denominator of the weight is the difference between the per capita GNP of the richest and poorest (index *u* and *l*, respectively) recipients, while the numerator is the difference between the richest recipient and recipient *i*. Clearly, the weights increase as per capita GNP decreases: from zero for the richest recipient to one for the poorest, which ensure the measure is sensitive to detect vertical inequity as defined in this context.

The index proposed is simply a weighted sum of the share of the aid allocated to each recipient where each recipient's allocation is weighted by its relative GNP per capita as compared with the GNP per capita of the other recipients. Applying this index to the health care delivery, would imply computing the weighted sum of the share of health care of each individuals, weighted by the relative need level as compared with the need of other individuals. This is analogous to the computation of the concentration index where individuals' shares of health care are weighted by their position in the rank of the need variable in the population. This would therefore provide a measure of how much health care is concentrated with respect to needs, but it would not be able to discern whether that concentration is appropriate or not. Therefore, it does not provide any advantage over the methods already discussed.

4.4. Conclusions

In this chapter we have reviewed, summarised and critically assessed the empirical literature on vertical equity in the delivery of health care. The methods identified were classified into different approaches and then the validity of each of them was assessed. Sutton, 2002 approach was found to provide the most comprehensive analysis of vertical equity in the delivery of health care to date. However, this approach was developed to measure the socioeconomic dimension of vertical equity alone. Further work to extent this methodology to ensure that the consequences across the need distribution are accounted for is considered necessary. Alternative ways of selecting the target allocation of health care will also be assessed in the following chapters of the thesis.

In addition to this, the literature on the methods applied to other fields to measure vertical equity was explored. Five areas were reviewed and the applicability of their methodologies to the context of health care delivery was assessed, alongside considering whether they provide an advantage over the methods available in health care. In most cases the methodologies focus on the vertical redistribution of one variable after a policy has been implemented and they had therefore little relevance in the context of measuring vertical equity in the distribution of health care. None of the remaining approaches were considered to provide any advantage over the methods already been used or proposed in the context of vertical equity in health care.

In the following chapter we will illustrate the most comprehensive methodology for the measurement of vertical inequity identified in this review. We apply the techniques proposed by Sutton, 2002 for the measurement of income-related horizontal and vertical inequity in cardiovascular disease (CVD)-related health care utilisation in England by individuals reporting a history of CVD.

CHAPTER 5

Income-related vertical inequity in health care utilisation among individuals with cardiovascular diseases in England

5.1. Introduction

The aim of this chapter is to measure vertical equity in health care utilisation in England using the most comprehensive techniques identified in the literature and proposed by Sutton, 2002. We use the concentration index approach to quantify income-related horizontal and vertical inequity in cardiovascular disease (CVD)-related health care utilisation in England by people reporting a history of CVD.

Sutton, 2002 focused on the measurement of socioeconomic-inequity in GP contacts in Scotland. While we use a similar approach, this analysis extends Sutton's in a number of ways. First, we look at utilisation of eight different types of health care contact and procedures – not just GP contacts. This allows us to examine whether or not the nature and extent of inequity is different for different types of use, allowing us to draw a full picture of inequity in health care provision. Secondly, we apply a decomposition approach to the inequity estimates to try and explain, as well as measure, inequity in health care utilisation. Thirdly, we explore alternative target allocation functions of health care use based on the relationship observed in subgroups of the population less likely to be affected by vertical inequity. Additionally, various econometrics techniques are applied in order to reduce unobserved reporting heterogeneity in the need measures as well as to explore potential endogeneity problems between health care utilisation and reported health problems.

In our analysis, we focus on CVD-related use of health services rather than use for any cause. The focus on CVD allows us to use disease-specific health measures that are more likely to capture need for disease-specific health care resources (van Doorslaer *et al.*, 2006). The cost of this approach is though highlighted by Propper *et al.*, 2005 who argue that *“the results will apply only to a single particular condition, which means the condition must be one that a large number of individuals suffer from and on which considerable public and private resources are spent”.* CVD is a major cause of mortality and morbidity in England; over 180,000 people die from CVD in the UK in 2009 (British Heart Foundation, 2010). There is also evidence of socioeconomic inequality in CVD incidence and mortality (O’Flaherty *et al*., 2009). According to the Programme Budgeting Data analysis of expenditure by disease programme[11], the NHS spent £8 billion on circulatory problems in 2009/10 making it the second largest area of programme expenditure after mental health.

The chapter is structure as follows. The Methods section describes in more details the approach suggested by Sutton, 2002 for the measurement of vertical inequity. In addition, we adapt the techniques for the decomposition of inequality to be applied to the decomposition of vertical inequity. Section 5.2 summarises the data and the statistical approach, alongside with the approach taken for the estimation of the appropriate effect of the need indicators. The results section presents the empirical results with respect to the econometric models, the equity estimates and the decomposition results. The last section summarises the main findings and highlights areas of further work.

5.2. Methods to measuring socioeconomic–related vertical equity

5.2.1. Measuring income-related vertical equity

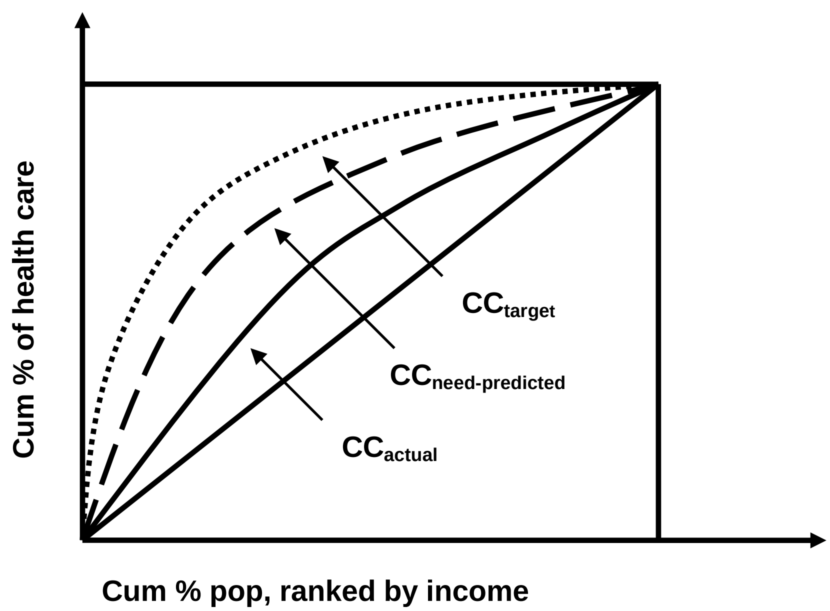
The concentration index approach is now widely applied to measure horizontal inequity in the delivery of health care. The methodology was presented and illustrated in Chapter 3 in this thesis. As previously noted, a major limitation of concentrating solely on horizontal inequity is that it ignores the possibility that the estimated differential treatment received by individuals with different needs is inappropriate, i.e., vertical inequity aspects. Sutton, 2002 challenged the assumption underpinning equity analyses that solely focus on horizontal inequity, which have been summarised as ‘*on average the system gets it right*’ (van Doorslaer *et al*., 2000). He criticised this assumption, especially in the context of comparing inequity indices across regions, countries or over time. As he highlights; ‘*[i]n international comparisons the vertical equity assumption becomes ‘on average, all*

[11] http://www.dh.gov.uk/en/Managingyourorganisation/Financeandplanning/Programmebudgeting/

systems get it right, possibly in different ways'. In time-series comparisons, this means 'on average, the system gets it right each year, possibly in different ways'.

He showed how the concentration index approach can be used to explore the magnitude of socioeconomic-related vertical inequity. Graphically, Figure 5.1 summarises the concentration curves for actual and need-predicted allocation similar to those discussed in Chapter 3. Recall that the divergence between these two curves shows the extent of income-related horizontal inequity. In order to quantify income-related *vertical* equity, Sutton proposed comparing the need-predicted curve with the curve resulting from a target distribution of health care (CC_{target} in Figure 5.1). The target allocation of health care is derived from the predicted values of the health care equation where the need variables have the optimal (or vertically equitable) effect on health care use. In his analysis, he created the target allocation by imposing a linear and positive relationship between levels of morbidity and utilisation found at low levels of morbidity to the whole sample and neutralising the effect of the non-need variables in the prediction.

Figure 5.1. Concentration curves of actual, need-predicted and target utilisation with respect to income



The target health care allocation is given in Equation (5.1),

$$q_i^* = \alpha^* + \sum_k \beta_k^* N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij} + \varepsilon_i \qquad (5.1)$$

Income-related vertical equity is then measured as the difference between the concentration of need-predicted and target health care with respect to income, i.e. the divergence in the allocation of health care that relates only to the difference between the actual effect and the appropriate effect of the need variables. When the concentration curve of need-predicted use lies below (above) the concentration curve of target use, there is vertical inequity favouring the rich (poor). Figure 5.1 thus illustrates the case of a pro-rich estimate of vertical inequity. Analogous to the horizontal inequity measure, we quantify vertical equity as twice the area between the target and the need-predicted concentration curves, or equivalently as the difference between the CI of the need-predicted allocation and the CI of the target allocation:

$$VI = 2 * \int [CC_{target} - CC_{need-predicted}] = CI_{\hat{q}} - CI_{q^*} \qquad (5.2)$$

Alternatively, the vertical equity estimate can be computed using the standardisation approach based on the CI of the difference between the need-predicted and the target health care variables plus the mean of the target allocation (in order to ensure that need-predicted and standardised health care use have the same mean)[12],

$$\begin{aligned} q_i^{VI} &= G(\hat{\alpha} + \sum_k \hat{\beta}_k N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij}) \\ &- G(\alpha^* + \sum_k \beta_k^* N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij}) \\ &+ \frac{1}{n} \sum_{n=1}^{n} G(\alpha^* + \sum_k \beta_k^* N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij}) \end{aligned} \qquad (5.3)$$

The index of vertical equity can be computed based on the concentration index of the variable derived from Equation (5.3). As previously discussed, the boundaries of the CI lie

[12] Note that as discussed in Chapter 2, the standardisation approach applied in the context of non-linear utilisation models rely on an approximation. This is because the effect of the non-need variables cannot be entirely neutralised by setting them equal to any given value as the prediction would depend on the value taken by all the covariates.

between -1 and +1; and a positive (negative) value indicates pro-rich (pro-poor) vertical inequity, i.e. the health care allocated to the rich (poor) according to the estimated effect of the need variables is proportionally higher than what would be allocated according to the target effect of the need variables. This would be the case, for instance, if the estimated effect of the need variables on use were lower (higher), in absolute terms, than the optimal and needs were concentrated on poorer groups of the population.

The total income-related inequity in health care is measured as the difference between the concentration index of the actual and the target allocation of health care; or equivalently as the sum of the horizontal and vertical inequity estimates,

$$TI \;= 2 * \int [CC_{t\arg et} - CC_{actual}] = CI_q - CI_{q^*} = \left[CI_q - CI_{\hat{q}}\right] + \left[CI_{\hat{q}} - CI_{q^*}\right] \qquad (5.4)$$

Therefore, income-related inequity in health care can be partitioned into the inequity derived by the effect of non-need variables in the allocation (horizontal inequity) and by the inequity due to the inappropriate effect of the need variables in the allocation (vertical inequity); each of these components having different implications for policy design. Using the standardisation approach, the index can be computed as the CI of the target-standardised allocation of health care defined as the difference between the actual and the target allocation of health care plus the mean of the target variable,

$$q_i^{TI} = q_i - G(\alpha^* + \sum_k \beta_k^* N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij}) + \frac{1}{n} \sum_{n=1}^{n} G(\alpha^* + \sum_k \beta_k^* N_{ik} + \sum_j \hat{\delta}_j \overline{Y}_{ij}) \qquad (5.5)$$

Similarly to any concentration index, the CI of this variable lies between -1 and +1, with a positive (negative) value indicating pro-rich (pro-poor) income-related inequity overall. Note that the sum of the vertical and horizontal inequity estimates could never exceed the boundaries of the total inequity estimate. The intuition is given by the fact that if, for instance, the horizontal inequity estimate was +1, the index of vertical inequity cannot take a positive value. This is because the target allocation could not estimate that proportional more health care should be allocated to the poorest part of the distribution than what the need-predicted allocation estimates, as the need-predicted allocation already estimates that all health care should be given to the poorest person.

Note that this measure of overall income-related inequity continues to focus on deviations of the vertical and horizontal equity principles with respect to the socioeconomic dimension. However, as compared with the analysis of horizontal inequity alone which only considers deviations of actual care from the average care received by individuals with equal needs, this measure of total income-related inequity also account for deviations of the average care received by individuals with different needs from the target care that these individuals should receive in order to meet the vertical equity principle.

Our measures of health care utilisation are all based on binary outcomes, and thus bounded between 0 and 1. Therefore the measurement of the CIs may be affected by the mean dependency problem (Erreygers, 2009). We apply the correction proposed by Erreygers to all our inequity estimates which ensures the normalisation of the indices.

5.2.2. Decomposing income-related vertical inequity

Recall that in Chapter 3 we describe how the decomposition property of the concentration index can be used to identify the sources of horizontal inequity (Wagstaff *et al.*, 2003). Van Doorslaer, *et al.*, 2004 have shown how the concentration index for need-standardised utilisation is equal to that which is obtained by subtracting the contributions of all need variables from the concentration index of actual health care. Horizontal inequity could thus be computed as the difference between the concentration index of actual health care allocation minus the contribution of the need variables.

By extension of this property, the vertical equity estimate could be computed as the difference between the sum of the contribution of the need variables based on their estimated effect and the sum of the contribution of the need variables based on their appropriate effect. We summarise this in Equation (5.6):

$$VI = \sum_k (\hat{\beta}_k - \beta_k^*) \frac{\overline{N}_k}{\bar{q}} CI_k \tag{5.6}$$

Therefore, we propose to use this property to investigate the sources of vertical inequity, by disentangling the individual contribution of each of the need indicators to the estimated vertical inequity. This will provide some insights about the specific need indicators which are responsible of the estimated vertical inequity. For instance, we might find that while the distributional consequences of the divergence between the actual and the appropriate effect of health status and gender on use are quite small, most of the estimated vertical inequity is due to the inappropriate effect of the age variable. The decomposition of the sources of vertical inequity can thus be instrumental for policy design.

Similar to the horizontal inequity case, in the context of non-linear models the results based on the decomposition are generally not identical to those that are obtained by alternative methods such as the standardisation technique. The reason being that the former approach relies on an approximation in order to compute the marginal effects[13].

We apply the standardisation approach to compute the indices of horizontal, vertical and overall inequity, but use the decomposition approach to disentangle the individual contribution of each of the need and non-need variables to the inequity estimates of each type of health care utilisation. As noted above, we apply the correction proposed by Erreygers, 2009 to the concentration index measures and the decomposition of the CI still holds when using this correction.

5.3. Exploring income-related vertical inequity using the Health Survey for England

5.3.1. Data

The analysis is based on data from two rounds (2003 and 2006) of the *Health Survey for England* (HSE) (National Centre for Social Research and University College London). In the most recent years of the HSE, the questions on health care utilisation are limited to specific subgroups of the population. The 2003 and 2006 surveys focused on CVD and a detailed set of question regarding CVD-related health measures were asked to adults aged over 16 year old who report having a history on CVD problems, alongside with health care utilisation data specifically for CVD. We focus on this sample that provide comprehensive information and allows us to link disease-specific measures of health care

[13] We estimate the marginal effects computing the average of the marginal effects of each observation using their specific covariates values rather than the marginal effect evaluated at the sample means.

need with disease-specific health care utilisation. The pooled sample consists of 10,254 individuals (5,692 in 2003 and 4,562 in 2006).

5.3.2. Measurement of needs

We require measures of CVD treatment need. Using data on age, gender and morbidity indicators as measures of needs is common practice in empirical investigation of inequity in health care utilisation. We use health status as the measure of needs assuming that individuals with worse CVD health are in higher needs for treatment and have a higher capacity to benefit from it. Note that all individuals in our sample report a history on CVD problems and therefore our measure of need can be thought to capture the severity of the condition or a degree of need. We will use the concepts of 'need' and 'health' equivalently.

Our measure of health is based on the EQ-5D. Information on EQ-5D (The Euroqol Group, 1990) is available in both years of our HSE data. This is a generic measure of health status based on self-reported responses to limitation in five dimensions (see Chapter 2 for a detailed description of this health measure). Although EQ-5D provides a comprehensive measure of health status that is widely recommended and employed, there are two potential concerns for its use in this analysis. First, the main concern of using self-reported health measures is the subjective nature of responses. This may lead individuals with identical underlying health status to report different levels of health, which in some cases may reflect systematic reporting heterogeneity between different groups. Secondly, in this paper we explore inequities in CVD-related use, and therefore, we require a measure of health status that reflects variation in health due to the impact of CVD problems and not due to other aspects of individuals' ill health. The richness of the data used in this chapter allow us to try and account for these potential issues by minimising reporting bias as well as removing the effect of other conditions in the estimation of our CVD-related need measure.

A proposed solution when we face unobserved reporting heterogeneity is to use a latent variable approach to predict health status based on the effect of objective measures of health, and to control for the effect of socioeconomic indicators in the reporting behaviour of health status (Kerkhofs & Lindeboom, 1995). Physician-diagnosed variables would be the ideal measures of objective health, but those are not commonly available and studies which have applied this approach often rely on reported specific health problems as a proxy of objective health measures. We exploit the richness of our data that contain information on doctor-diagnosed conditions and symptom-based indicators of CVD problems, as well as objective measures of health collected during a subsequent nurse visit. In order to control for the effect of other health conditions, we include indicators for the presence and number of 15 types of longstanding illnesses as well as interactions between those conditions and the reported CVD problems. We hence create a need index, summarised in Equation (5.7), derived by regressing EQ-5D scores against a comprehensive set of doctor diagnosed, symptom based, objective measures of CVD-related health, and interactions with other diseases, in addition to the presence and number of other health conditions denoted by *O*, and socioeconomic characteristics denoted by *S*. Then, we predict health status keeping all the other health conditions and socioeconomic indicators at the sample mean values, so only the effect of the CVD health indicators and comorbidities is allowed to vary between individuals.

$$EQ5D = \alpha + \beta_1 Doctor + \beta_2 Symptom, + \beta_3 Objective + \beta_4 Interaction + \beta_5 \overline{O} + \beta_6 \overline{S} \quad (5.7)$$

Note that although our sample by design is composed by individuals reporting CVD, other health conditions the individual may suffer from would have a direct and independent effect on health over and above the individual CVD problem. In addition, comorbidities may also increase the severity of CVD or the patient's ability to manage the condition and hence affect their need for CVD-related health care. By including interactions between the specific CVD problems and other diseases in addition to the individual indicators we try and isolate such interactions from the direct effect of these diseases on health status, the latter being the effect we aim to neutralise. It is also worth noting that preserving the socioeconomic indicators as predictors of reporting bias is equivalent to assuming that, after controlling for health measures, variation in self-reported health status across different socioeconomic groups reflects reporting bias and not genuine variation in health. If the model were not adequately controlling for CVD-related health this approach may also be reducing the extent of socioeconomic variation in CVD needs in our population. We think our approach is appropriate given the richness of our health measures. This is also the approach taken in previous studies (Jones *et al.*, 2010; García-Gómez *et al*., 2010), which aim to create a measure of health purged from reporting bias.

The CVD-related indicators are: CVD risk factors (smoking status, obesity, gender, age (measured as a cubic function), and family history of CVD); health measures collected in the nurse visit (cholesterol level, blood pressure and glycated haemoglobin level); doctor-diagnosed CVD-related problems (type 1 diabetes, type 2 diabetes, angina, heart attack, and stroke); symptom-based CVD factors (grade 1 or grade 2 angina based on the World Health Organisation Rose Questionnaire, (Rose & Blackburn, 1986), and whether or not respondents had a possible myocardial infarction, a sudden attack of weakness or numbness on one side of the body, a sudden attack of slurred speech or difficulty in finding words, or a sudden attack of vision loss or blurred vision in one or both eyes in the last 12 months). We include symptom-based variables because they can capture unexpressed needs for health care among those not diagnosed due to their lack of contact with the health care system (Asthana *et al.*, 2004). We also include indicators for whether the individual reported having heart murmur, abnormal heart rhythm, high blood pressure or any other heart trouble. The list of questions in the HSE relating to these indicators is presented in Appendix 5.1. We restrict the model to include only statistically significant variables at a 5% significance level. We test for multicollinearity using variance inflation factors (VIFs) (Chatterjee & Hadi, 2006).

5.3.3. Measurement of income

We proxy socioeconomic status (SES) by predicted household income. Similar to the approach taken in previous chapters, we regress annual household income reported in 31 income bands, against a set of individual and household socioeconomic characteristics using an interval regression model. We use the regression coefficients to predict annual household income as a continuous variable for the respondents in the sample with non-missing income data. The predicted values were constrained to fall within the income band originally selected by the respondent. We also used the interval regression model to make out of sample predictions to impute the income variable for individuals who did not report their household income (around 17% of the sample). All the predicted income values were equivalised using weights provided in the HSE to account for household composition, and then transformed into natural logarithms[14].

[14] We experimented with using multiple imputation techniques using the – *mice* – command in stata, rather than a single equation approach in the imputation of missing income values. The methods yielded similar results for those analyses that were compared and therefore we kept the single equation approach given the large set of analyses that are undertaken in this study and the time consuming nature of running the multiple imputations.

5.3.4. *Models of health care utilisation*

The analyses include the following eight health care contacts:

- Talking to a doctor in the previous two weeks;
- Visiting a practice nurse in a GP practice in the last two weeks;
- Having an outpatient visit during the last 12 months;
- Having an inpatient stay in the last 12 months;
- Having high blood pressure currently being monitored by a GP/nurse/other doctor;
- Currently receiving regular check-ups or monitoring because a heart condition;
- Ever having an electrical recording of the heart (ECG);
- Ever having any surgery or operation because of a heart condition.

Most of the health care contacts questions were asked to the full sample of individuals reporting any CVD condition, but the probability of having blood pressure monitored by a GP/nurse/other doctor is only relevant for those reporting high blood pressure, and having regular check-ups or heart surgery was only asked to those who had angina, heart attack, stroke, irregular heart rhythm or 'other heart trouble'. Most types of contacts were related to the respondents' CVD condition, and where they may not have been this was recorded and we did not use these contacts. The questions from the HSE are in Appendix 5.1. Health care utilisation is measured as a binary variable (1= yes; 0 otherwise). In the case of doctor and nurse visits the numbers of visits are recorded, but very few respondents had more than one visit to see either the practice nurse or the doctor (0.52% and 1.02% of the sample, respectively) and so we model use of these services as a binary outcome.

We try to allow the different utilisation models to be correlated using simultaneous equation estimation models as explained in Chapter 3. However, given the differences in the time frame and the samples used with respect to the utilisation questions, we could only account for the potential correlation between doctor and practice nurse visits, and inpatient and outpatient visits, separately. Similarly to the results shown in Chapter 3 of this thesis, the inequity estimates derived from the models that accounted for correlation using bivariate probit models were very similar to the univariate model results (see Appendix 5.2). Therefore, and for consistency across the models undertaken in this study, we report the results using univariate probit regression models throughout.

The models for health care utilisation include a series of need and non-need variables. The need variables in our models are gender, a cubic function of age and our CVD-specific health index. Note that age and gender indicators were also included as covariates to predict the need index; however, these variables might have a legitimate direct effect on utilisation over and above their impact on health status, and are thus included as explanatory variables of health care use separately. A number of non-need indicators and control variables commonly included in health care utilisation regression analysis literature are also included. These are household income, education (measured by whether the individual is educated to a degree level or higher), marital status (measured by whether the individual is married), ethnicity (measured by whether the individual belong to White ethnic group), place of residence (defined by the Government Office Region (GOR) of residence) and year of data. Compared with the set of covariates included in the analysis of Chapter 3, the number of variables is reduced and simplified given the smaller sample size in this study. Supply information could not be linked to the individual HSE data as the only area of residence identifier available in these year of data were the GORs.

We experimented with including the CVD need variable up to the fifth degree polynomial term in the utilisation models, both in the full models and the targets groups. We allowed the functional form to vary for each type of use and only retained significant non-linear terms. For consistency across the models we present only the results where the need variable is included as a linear term. When we allowed the need variable to take any significant functional form the vertical inequity estimates were very similar to those that imposed linearity (results are presented in Appendix 5.3). This is partly because the utilisation functions were approximately linear across most of the range of the need variable (we found evidence of non-linearity mainly at the bottom end of the need distribution affecting a very small percentage of the sample) and partly because non-linearity was captured by the functional form imposed by the probit models.

5.3.5. Finding the target effect of the need variables

Our approach to selecting target use at each level of need differs from that used in previous studies. Sutton, 2002, derives the target function by imposing the negative linear effect of health on use found in one part of the health distribution (among the healthy) on to respondents across the whole health distribution. This imposes the restriction that the relationship between changes in health and changes in use among the unhealthy ought to be the same as this relationship among the healthy. Furthermore, the underlying requirement for choosing this target was that the effect of the health variable ought to be negative across the full range of the health distribution. However, as noted in Chapter 3, the imposition of a strictly negative effect of health on utilisation may not be appropriate for specific types of services or patients. We adopt a slightly different approach, which we believe is better evidenced. Our method is based on sub-groups of respondents taken from across the health distribution who have been shown in previous studies to be less likely to be affected by unmet health care needs. We then apply the relationship between changes in health and changes in use among respondents in these sub-groups, who are drawn across the whole health distribution, to other individuals not in these groups, who are also spread across the health distribution.

Our selection of the ‘target groups’ is based on the idea that there are systematic unmet needs for some groups of the population, and therefore the estimated effect of needs on health care may be biased downward in these groups. Evidence shows that even in countries with universal health care coverage, better-off individuals are less likely to have unmet needs; ‘foregone health care’ has been found to be positively associated with low income and lower education attainment (Elofsson *et al.*,1998; Westin *et al.*, 2004; Koolman, 2007; Mielck *et al.*, 2007). We use the richest and the most highly educated respondents in our sample as target groups. These are defined as the richest 50% of the sample and those educated to degree level or higher, respectively. Note that these target groups are expected to use health care when they need it but, in addition, they should also receive low levels of care when they are in low needs.

We explore the sensitivity of our results by dropping the richest 5% of the population in the income target group, and by including those with any type of qualification in the education target group. Although the sizes of the estimates varied, the results yielded the same conclusions as reported in the results section (results are presented in Appendix 5.4).

5.3.6. Sampling issues

All models use sample weights reported in the HSE and are adjusted for clustering at the Primary Sample Unit (PSU) level using unique PSU/year identifiers. By allowing observations within PSUs not to be independent of each other we recognise that a series of unobserved household and area characteristics may affect health care utilisation, such as the availability of health care supply in the area. To maximise the sample size we imputed missing values. Missing values for income were imputed as explained above. For binary and categorical variables, missing values were assigned to the omitted category. To allow for the possibility that items were not missing at random we included dummy variables for all imputed items to indicate item non response.

As highlighted in Chapter 3, the methods traditionally employed to compute standard errors (SE) around the horizontal inequity estimates ignore the extra uncertainty introduced by the fact that the need-predicted variable is derived from the predicted values of a regression model. The implications for the vertical equity estimate are even more pronounced as this estimate is derived from the difference between two predicted variables, i.e. the need-predicted and the target allocation of health care. Therefore, in our analyses, standard errors around the inequity point estimates and the contribution of the explanatory variables in the decomposition analyses are computed using bootstrapping techniques based on 500 replications, including the estimation of the regression models for the need-predicted and the target allocation within the bootstrapping process.

5.4. Empirical results

5.4.1. Health and income models

Table 5.1 shows the results of the reduced EQ-5D regression model. The CVD indicators have a negative effect on health and most of the other reported longstanding illnesses also affect significantly and negatively the EQ-5D scores. Note that controlling for having a doctor diagnosis of angina or stroke does not remove the effect of the equivalent symptom-based variables, which are individually and strongly significant.

These symptom-based variables may capture variation in severity of the doctor-diagnosed conditions; or alternatively, their effect might suggest that some individuals with these problems that deteriorate their health significantly have not yet been diagnosed, which support the unexpressed need for health care assumption.

Table 5.1. OLS model of EQ-5D on health and socioeconomic indicators

	Mean	SD	Coef	z
CVD-indicators				
Age/100	0.521	0.173	-0.082	-3.74
Age-squared/10000	0.302	0.183	0.120	1.51
Age-cubed/1000000	0.189	0.162	-0.793	-2.66
Smoker	0.229	0.420	-0.035	-6.94
Obesity	0.283	0.451	-0.028	-6.63
Type 1 diabetes	0.011	0.103	-0.044	-2.29
Type 2 diabetes	0.072	0.259	-0.052	-6.26
Doctor-diagnosed angina	0.073	0.260	-0.028	-3.00
Doctor-diagnosed stroke	0.040	0.195	-0.055	-4.50
Symptom angina grade 2	0.013	0.113	-0.110	-4.80
Possible myocardial infarction	0.135	0.342	-0.044	-6.16
Symptom weakness	0.075	0.264	-0.108	-10.17
Symptom slurred speech	0.047	0.211	-0.065	-4.54
Symptom vision lost	0.114	0.318	-0.037	-5.44
Heart murmur	0.086	0.280	-0.021	-2.92
Irregular heart rhythm	0.165	0.372	-0.033	-5.93
High blood pressure	0.575	0.494	-0.010	-2.64
Other heart trouble	0.045	0.207	-0.022	-2.23
Myocardial infarction + respiratory condition	0.0001	0.009	-0.052	-2.50
High blood pressure + musculo-skeletal condition	0.024	0.153	-0.035	-3.11
Diabetes type 1 + neoplasms & benign growths	0.149	0.356	-0.382	-9.83
Other health conditions				
Neoplasms & benign growths	0.025	0.155	-0.100	-6.28
Blood & related organs	0.011	0.103	-0.075	-3.33
Mental disorders	0.046	0.209	-0.211	-15.55
Nervous system	0.052	0.223	-0.135	-11.86
Respiratory system	0.103	0.304	-0.037	-4.72
Digestive system	0.065	0.246	-0.060	-6.31
Genito-urinary system	0.033	0.178	-0.043	-3.58
Musculo-skeletal	0.247	0.431	-0.193	-21.97
Socioeconomic indicators				
Log household income	9.863	0.978	0.023	9.08
Educational degree	0.159	0.366	0.017	3.73
Ethnic group white	0.928	0.258	0.016	1.89
Marital status married	0.578	0.494	0.010	2.21
N		10,263		

Note: Coeff = Coefficient; SD = Standard Deviation

Model control for year of data and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level

The effects of socioeconomic indicators show that richer, better educated, white and married individuals tend to report better health status after controlling for their health conditions.

It is worth noting that the objective measures of health were only available for a small proportion of the sample. The reason is that only about half of the sample had valid measures of haemoglobin levels and a similar number had valid blood pressure and cholesterol level values. In practice though, these variables were not found to have a significant effect on the EQ-5D equation over and above the individual's reported and doctor-diagnosed CVD conditions, and are thus excluded from the model. This is consistent with earlier work that have found reporting a false negative for hypertension (defined as systolic/diastolic blood pressure equal or higher than 90/140mmHg in the nurse visit, but individual not reporting hypertension when asked about his/her longstanding illnesses) does not affect self-reported general health after controlling for the reported hypertension effect (Johnston *et al.*, 2009). Excluding the objective measure also allows us to use the full sample of individuals reporting a history of CVD problems.

Table 5.2 presents the results of the interval regression of household income. Most variables have the expected sign, with lower social class, lower education attainment, minority ethnic groups, and economic activity other rather than being in paid employment all being negatively correlated with household income. The multicollinearity tests in both the health and income models show that other than in the case of the age variables there were no signs of collinearity among the included covariates. The largest VIF for the remaining variables was 2.58 and 4.14 (lower than 10), in the health and income equation, respectively.

5.4.2. Socioeconomic inequity in health care utilisation for CVD

The results for the binary models of each of the eight types of CVD-related health care utilisation are in Tables 5.3 and 5.4. Summary statistics of the utilisation variables are presented in these tables; for each model we present the coefficient and marginal effect of each covariate (coefficients with two stars are significant at 5% and coefficients with one star are significant only at 10%).

Table 5.2. Interval regression model of household income on individual and household characteristics

	Mean	SD	Coeff	z		Mean	SD	Coeff	z
Age and sex					***Ethnic group***				
Female	0.549	0.498	-1390.7	-2.85	White	0.934	0.249	Base category	
Age/100	0.533	0.173	-17999.0	-3.97	Black Caribbean	0.013	0.115	-7191.2	-3.93
Age-squared/10000	0.314	0.187	-19412.5	-2.36	Black African	0.005	0.072	-1561.3	-0.27
Age-cubed/1000000	0.199	0.167	83005.1	2.14	Indian	0.015	0.122	-3249.8	-1.38
Social class of head of					Pakistani	0.008	0.088	-8674.9	-2.06
Professional	0.067	0.250	Base category		Bangladeshi	0.001	0.038	-18052.0	-3.87
Managerial/technical	0.330	0.470	-4482.1	-2.99	Chinese	0.001	0.036	-11378.8	-2.37
Skilled non-manual	0.149	0.356	-13513.2	-8.92	Other	0.013	0.113	-4123.8	-1.54
Skilled manual	0.237	0.425	-13537.7	-9.06	***Number of cars in household***				
Semi-skilled manual	0.144	0.351	-14407.8	-9.36	No car	0.220	0.414	Base category	
Unskilled manual	0.049	0.216	-14181.7	-8.89	One	0.435	0.496	1278.0	1.96
Other	0.023	0.150	-12179.7	-5.18	Two	0.272	0.445	11101.2	11.67
Economic activity					Three or more	0.073	0.261	23398.1	13.15
In paid employment	0.492	0.500	Base category		***Bedrooms per person***	1.373	0.704	833.3	1.76
Going to school/college full time	0.019	0.138	-3761.7	-1.90	***Marital status***				
Permanent long term sickness	0.065	0.246	-10284.1	-12.99	Married	0.588	0.492	Base category	
Retired from paid work	0.294	0.456	-6404.5	-7.05	Single	0.178	0.383	-4603.2	-4.63
Looking after the home	0.101	0.301	-3757.0	-3.46	Separated	0.015	0.121	-3300.0	-1.37
Waiting to take up paid job	0.003	0.053	-1784.0	-0.23	Divorced	0.064	0.244	-5467.2	-5.44
Looking for paid job	0.015	0.121	-10796.8	-5.77	Widowed	0.116	0.320	-5129.6	-7.00
Temporary sickness or injury	0.006	0.077	-12604.2	-4.60	***Housing tenure***				
Doing something else	0.001	0.033	-13921.6	-2.61	Own	0.350	0.477	Base category	
Education					Mortgage	0.379	0.485	5970.6	6.85
Degree	0.158	0.365	Base category		Part mortgage	0.004	0.065	1939.6	0.49
Higher education less than degree	0.121	0.326	-10870.2	-9.16	Rent	0.255	0.436	-945.6	-1.24
A level or equivalent	0.100	0.299	-9050.7	-7.27	Free rent	0.011	0.105	-3262.7	-1.48
GCSE or equivalent	0.221	0.415	-12039.6	-11.26					
CSE or equivalent	0.051	0.220	-13658.9	-10.99	σ			20530.73	485.90
Other qualification	0.036	0.187	-13458.9	-10.67	N			8,234	
No qualification	0.311	0.463	-12549.6	-11.55					

Note: Coeff = Coefficient; SD = Standard Deviation

Model control for year of data, GOR of residence and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level.

Table 5.3. Probit models for CVD-related utilisation among individuals with CVD (doctor, nurse, inpatient and outpatient)

	Doctor visit			Nurse visit			Inpatient visit			Outpatient visit		
	Coeff.	**ME**	**Cont.**	**Coeff.**	**ME**	**Cont.**	**Coeff.**	**ME**	**Cont.**	**Coeff.**	**ME**	**Cont.**
Health	-2.561**	-0.303	-0.0141**	-1.992**	-0.192	-0.0089**	-4.494**	-0.274	-0.0127**	-4.772**	-0.783	-0.0363**
Age/100	1.871**	0.222	-0.0195**	1.814**	0.175	-0.0154**	0.943**	0.058	-0.0051**	1.019**	0.167	-0.0147**
Age2/10000	0.802	0.095	-0.0028	0.039	0.004	-0.0001	3.559**	0.217	-0.0064**	3.569**	0.585	-0.0172**
Age3/1000000	-12.49**	-1.481	0.0147**	-10.71**	-1.035	0.0102**	-10.21**	-0.623	0.0062**	-15.75**	-2.585	0.0256**
Female	-0.017	-0.002	0.0002	-0.047	-0.005	0.0005	-0.109**	-0.007	0.0007*	-0.219**	-0.036	0.0039**
Log income	0.007	0.001	0.0016	-0.018	-0.002	-0.0033	0.031	0.002	0.0037	0.055**	0.009	0.0176**
Educational degree	-0.002	0.000	-0.0001	-0.108	-0.010	-0.0031	0.195**	0.012	0.0035**	0.147**	0.024	0.0071**
Ethnic group white	-0.257**	-0.030	-0.0009**	-0.215**	-0.021	-0.0006*	-0.095	-0.006	-0.0002	-0.193**	-0.032	-0.0009
Married	0.034	0.004	0.0007	0.106**	0.010	0.0019**	-0.022	-0.001	-0.0002	-0.016	-0.003	-0.0005
North East	-0.089	-0.011	0.0005	0.164	0.016	-0.0007*	-0.009	-0.001	<0.0000	-0.107	-0.018	0.0008
North West	-0.129	-0.015	0.0007	0.096	0.009	-0.0004	-0.031	-0.002	0.0001	-0.098	-0.016	0.0007
Yorkshire	-0.213**	-0.025	0.0005	0.123	0.012	-0.0002	-0.084	-0.005	0.0001	-0.067	-0.011	0.0002
East Midlands	-0.307**	-0.036	0.0006*	0.097	0.009	-0.0002	-0.148	-0.009	0.0002	-0.143*	-0.023	0.0004
West Midlands	-0.189**	-0.022	0.0009*	0.098	0.009	-0.0004	-0.070	-0.004	0.0002	-0.052	-0.008	0.0003
East of England	-0.194**	-0.023	-0.0005	-0.058	-0.006	-0.0001	-0.181	-0.011	-0.0002	-0.034	-0.006	-0.0001
South East	-0.142*	-0.017	-0.0017*	-0.009	-0.001	-0.0001	-0.205**	-0.013	-0.0012**	-0.135*	-0.022	-0.0022*
South West	-0.199**	-0.024	-0.0141	0.015	0.001	<0.0000	-0.294**	-0.018	<0.0000	-0.342*	-0.056	<0.0000
Residual			0.0004			-0.0064**			-0.0027**			0.0014
Mean (SD)	0.064 (0.245)			0.049 (0.216)			0.032 (0.175)			0.108 (0.31)		
N	10,263			10,263			10,263			10,259		

Note: Coeff = Coefficient; ME = Marginal effect; Cont. = Contribution to inequality. Coefficients and contributions with two and one star are statistically significant at 5% and 10% significance level, respectively. Standard Errors in the decomposition analyses computed using bootstrapping techniques. Models control for year of data and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level.

Table 5.4. Probit models for CVD-related utilisation among individuals with CVD (monitor BP, check-ups, ECG and surgery)

	Monitor BP			Regular check-ups			ECG test			Surgery		
	Coeff.	ME	Cont.	Coeff.	ME	Cont.	Coeff.	ME	Cont.	Coeff.	ME	Cont.
Health	-0.973**	-0.342	-0.0169**	-3.626**	-1.135	-0.0667**	-5.422**	-1.815	-0.0843**	-2.254**	-0.503	-0.0300**
Age/100	3.268**	1.149	-0.1104**	3.430**	1.074	-0.1221**	2.586**	0.866	-0.0755**	1.951**	0.435	-0.0490**
Age2/10000	-2.085*	-0.734	0.0219*	3.842**	1.203	-0.0407**	2.095**	0.701	-0.0205**	3.420**	0.763	-0.0252**
Age3/1000000	-10.02**	-3.524	0.0367**	-22.38**	-7.005	0.0909**	-18.488**	-6.189	0.0606**	-18.256**	-4.073	0.0513**
Female	0.066**	0.023	-0.0036*	-0.299**	-0.094	0.0051**	-0.253**	-0.085	0.0092**	-0.474**	-0.106	0.0056**
Log income	0.010	0.004	0.0070	-0.019	-0.006	-0.0120	0.043**	0.014	0.0283**	0.051*	0.011	0.0231
Educational degree	-0.036	-0.013	-0.0035	-0.049	-0.015	-0.0041	0.052	0.017	0.0051	-0.007	-0.002	-0.0005
Ethnic group white	-0.261**	-0.092	-0.0027	-0.071	-0.022	-0.0004	0.137**	0.046	0.0014	-0.061	-0.014	-0.0003
Married	0.047	0.017	0.0024	0.107**	0.033	0.0054**	0.045	0.015	0.0027*	0.093	0.021	0.0032
North East	0.075	0.026	-0.0013	0.218*	0.068	-0.0033*	0.027	0.009	-0.0004	-0.181	-0.040	0.0022
North West	0.103	0.036	-0.0015	0.225**	0.070	-0.0019	0.000	0.000	<0.0000	-0.219*	-0.049	0.0014
Yorkshire	0.211**	0.074	-0.0016	0.124	0.039	-0.0015	-0.019	-0.006	0.0001	-0.183	-0.041	0.0015
East Midlands	0.173**	0.061	-0.0011	0.023	0.007	-0.0002	-0.095	-0.032	0.0006	-0.301**	-0.067	0.0020*
West Midlands	0.234**	0.082	-0.0029*	0.098	0.031	-0.0010	-0.054	-0.018	0.0007	-0.172	-0.038	0.0012
East of England	0.038	0.013	0.0003	0.115	0.036	0.0005	-0.015	-0.005	-0.0001	0.024	0.005	0.0001
South East	0.136*	0.048	0.0046*	-0.009	-0.003	-0.0003	-0.015	-0.005	-0.0005	0.053	0.012	0.0013
South West	0.108	0.038	-0.0002	0.041	0.013	<0.0000	-0.060	-0.020	<0.0000	-0.143	-0.032	-0.0002
Residual			-0.0146			-0.0006			0.0092*			0.0059
Mean (SD)		0.372 (0.483)			0.357 (0.479)			0.607 (0.488)			0.160 (0.367)	
N		6,702			3,792			10,215			3,455	

Note: BP = Blood pressure; Coeff = Coefficient; ME = Marginal effect; Cont. = Contribution to inequality. Coefficients and contributions with two and one star are statistically significant at 5% and 10% significance level, respectively. Standard Errors in the decomposition analyses computed using bootstrapping techniques. Models control for year of data and missing values. Sample weights are used and we adjust for clustering at Primary Sample Unit level.

Better levels of CVD health have a statistically significant and negative association with all types of CVD-related use. Age has a non-linear and significant effect in every type of use while gender is significant in every model with the exception of doctor and nurse visit utilisation. Income has a significant and positive association with outpatient visits and ECG tests. The effect of higher education attainment is also significant and positive in inpatient and outpatient visits. Non-white ethnic groups are significantly less likely to have an ECG compared with white groups, and are significantly more likely to have a doctor, nurse, and outpatient visit, and to receive blood pressure monitoring

Being married is positively related with the probability of having a nurse visit and also with the probability of receiving regular heart check-ups. After controlling for the other covariates included in the models, there is area variation in the probability of having a doctor visit, inpatient stay, outpatient appointment, high blood pressure monitoring and heart surgery.

The main results of the inequity analyses are summarised in Table 5.5. All types of use are concentrated in poorer groups of the population as shown by the negative CIs of actual health care utilisation. The horizontal inequity estimates show that after controlling for the average effect of the need indicators, relatively poorer individuals have proportionally more practice nurse consultations but they have less outpatient visits, ECG tests and heart surgery. For the remaining types of health care utilisation measures, the distribution appears to be horizontally equitable.

Moving to the results of vertical equity, Figure 5.2 provides a graphical representation of the effect of our proxy CVD-related health indicators on health care use in the full sample and in the different target groups for the case of doctor visits. Similar effects were found for the other types of contacts and figures are presented in Appendix 5.5. The probability of use is strictly decreasing with better health; however, for each of the target groups the needs gradient is steeper at higher levels of needs compared with the whole sample, indicating that those with higher needs have higher use than those not in these groups with the same levels of need. Additionally, those in the target groups use less health care than the average individual when they have good levels of health.

Table 5.5. Equity estimates of health care utilisation among individuals with CVD

		Doctor visit		Nurse visit		Inpatient visit		Outpatient visit	
		CI	CI/SE	CI	CI/SE	CI	CI/SE	CI	CI/SE
CI actual use		-0.0228	-4.07	-0.0281	-5.71	-0.0212	-5.39	-0.0249	-3.54
Horizontal inequity		0.0014	0.26	-0.0129	-2.65	0.0015	0.38	0.0239	3.53
Vertical inequity									
Target:	Richer 50%	0.0062	1.42	0.0062	1.64	-0.0005	-0.13	0.0056	1.25
	Having degree	0.0219	2.36	0.0137	1.39	0.0148	1.82	0.0282	2.70
Total inequity									
Target:	Richer 50%	0.0076	0.92	-0.0067	-0.99	0.0018	0.33	0.0295	3.14
	Having degree	0.0233	1.95	0.0007	0.06	0.0163	1.73	0.0521	3.90

		Monitor BP		Regular check-ups		ECG test		Surgery	
		CI	CI/SE	CI	CI/SE	CI	CI/SE	CI	CI/SE
CI actual use		-0.0897	-6.60	-0.1525	-8.57	-0.0545	-4.73	-0.0021	-0.14
Horizontal inequity		-0.0150	-1.09	-0.0142	-0.87	0.0498	5.73	0.0452	3.24
Vertical inequity									
Target:	Richer 50%	-0.0095	-1.24	0.0047	0.53	0.0096	2.05	0.0254	3.45
	Having degree	0.0091	0.45	0.0445	1.70	0.0287	2.37	0.0350	1.89
Total inequity									
Target:	Richer 50%	-0.0245	-1.36	-0.0095	-0.45	0.0594	4.84	0.0706	4.08
	Having degree	-0.0059	-0.23	0.0302	0.95	0.0784	4.47	0.0803	3.29

Note: CI = Concentration index; SE = Standard error; BP = Blood pressure; ECG = electrical recording of the heart; Standard errors are derived using bootstrapping techniques.

Figure 5.2. Effect of health variable on the probability of seeing a doctor in the last two weeks (full sample and target groups)

Probability of doctor visit

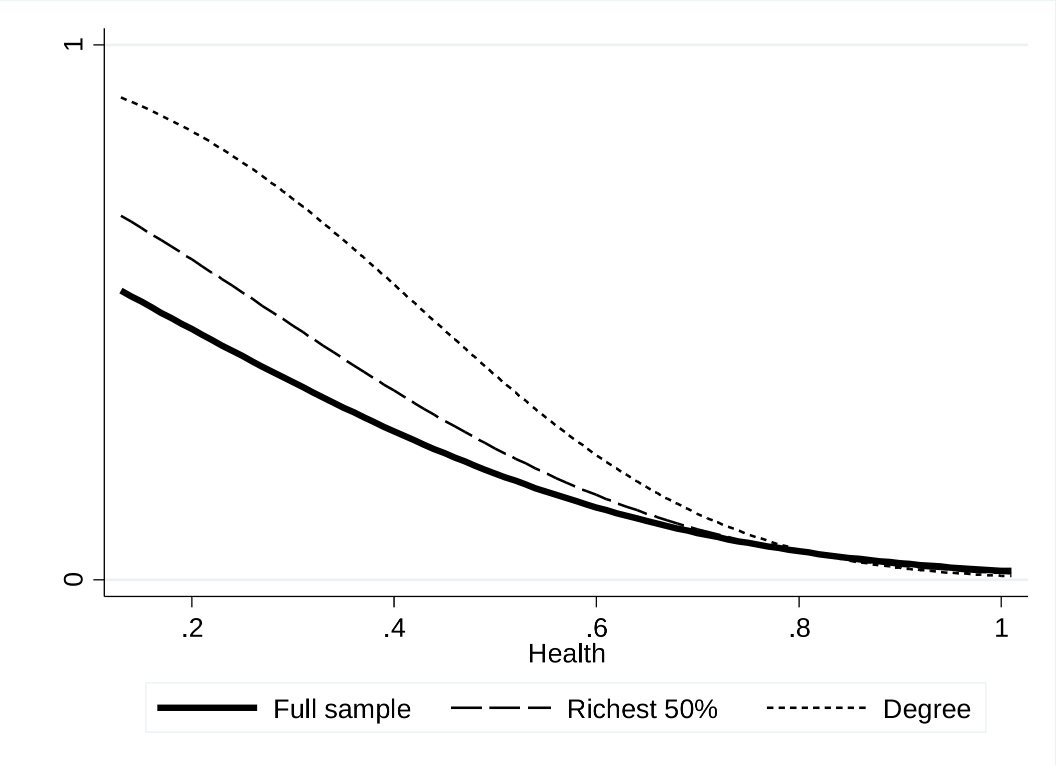


Table 5.6 shows the results for the formal test that the coefficients of the need variables (age, gender and CVD-related need) are statistically significantly different in the target groups than in the whole sample. We find that for four types of service use the effect of the needs variables among the richest 50% is different than that among the full sample (two of them weakly so) and among those with better educational attainment the effect is different in five out of the eight types of health care services (two of them weakly so). Appendix 5.6 shows the percentage of individuals in different parts of the health distribution based on our CVD-related need index in the full sample, in the richest 50% subgroup, and in the subgroup educated to a degree level. In every case, individuals are concentrated in relatively healthy values, although, as one would expect, a slightly lower percentage of individuals are concentrated in the sickest part of the distribution under each of the target groups than across the full population

The estimates for income-related vertical inequity are positive for most services and target groups, indicating that poorer groups have proportionally less need-predicted use than the estimated by the target (see Table 5.5). The only exceptions are the vertical equity estimate for the probability of having an inpatient stay and receiving monitoring for high blood pressure when using the richer 50% as the target group, but the estimates are not significant. The vertical inequity (VI) estimates are significantly pro-rich for doctor visits, outpatient visits, ECG test, inpatient visits and surgery (the last two only weakly significant) when the effect is estimated among those having an educational degree. The VI point estimates are larger using this target group than the richer 50%. Using the richer 50% target group, there is vertical inequity in ECG tests and heart surgery, and some weak evidence in the case of nurse consultations.

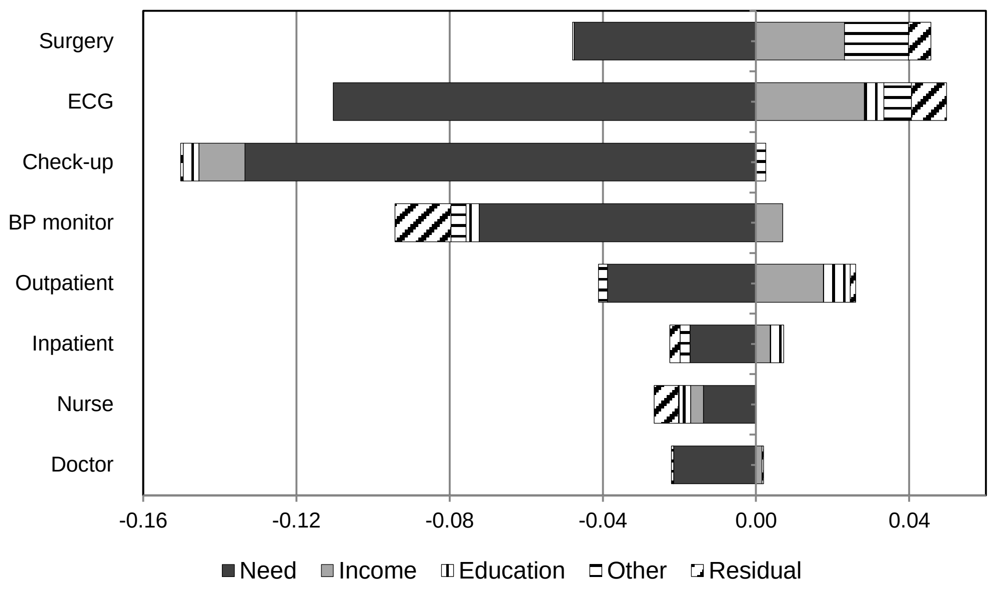
Table 5.6. Test for the coefficient of the need variables in full sample equal to those in target groups

	Richer 50%		Having degree	
	Chi-square	p-value	Chi-square	p-value
Doctor visit	5.81	0.325	12.32	0.031
Nurse visit	10.6	0.060	5.46	0.362
Inpatient visit	4.85	0.435	5.08	0.406
Outpatient visit	10.01	0.075	13.25	0.021
Monitor BP	2.31	0.805	5.17	0.395
Regular check-ups	4.02	0.547	10.34	0.066
ECG test	12.47	0.029	15.85	0.007
Surgery	26.13	0.0001	9.68	0.085

Compared with considering horizontal inequity alone, the total inequity estimates (horizontal plus vertical inequity) lead us in some cases to different conclusions about the nature and extent of income-related inequity in use (see Table 5.5). After accounting for vertical inequity, there is some evidence of inequity favouring the rich for doctor visits and inpatient visits, while the horizontal inequity estimates were in both cases non-significant. Practice nurse visits were found to be horizontally pro-poor, but after accounting for vertical inequity, the estimates of income-related total inequity show an equitable distribution across income groups. The estimates of income-related inequity for outpatient visit, ECG tests and heart surgery become even more pro-rich when accounting for vertical inequity; in some cases the total inequity estimates are more than double the size of the original estimates of horizontal inequity.

The results of the decomposition results provide some insights about the specific variables driving the inequity results. Table 5.3 and 5.4 present the contributions and its significance of each of the covariates included in the regression models to the observed inequalities in health care utilisation. Figure 5.3 provides a chart summarising these results graphically for ease of comparison across the different types of use. The individual contribution of each of the non-need indicator provides some evidence of the drivers of horizontal inequity, while the difference in the contribution of the need variables under the estimated and the target effect of each of the need indicators illustrate the sources of vertical inequity. The latter are represented graphically in Figure 5.4.

Figure 5.3. Contributions to total inequality in health care utilisation

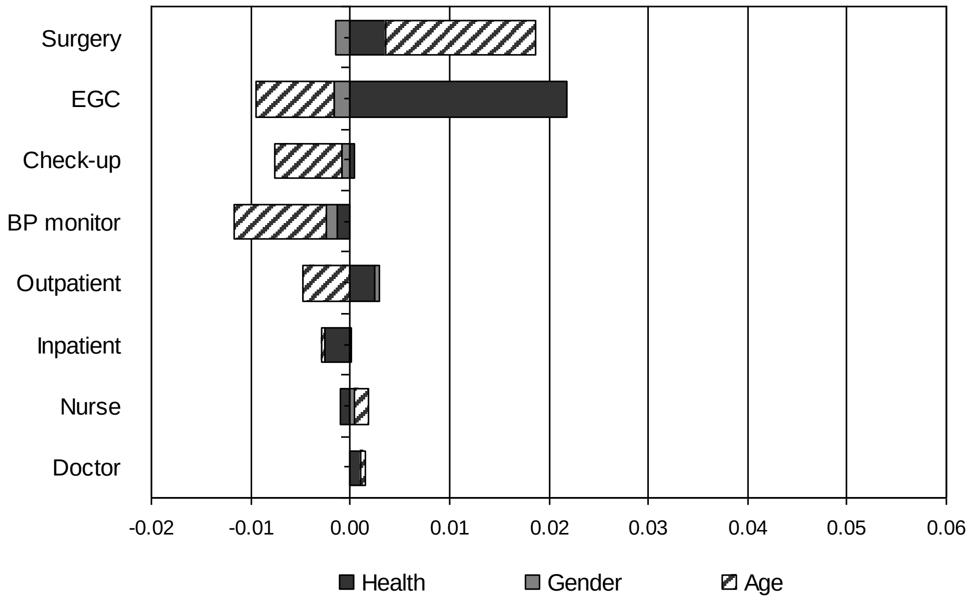


Note: Decomposition based on linear approximation using average marginal effects from a probit regression.

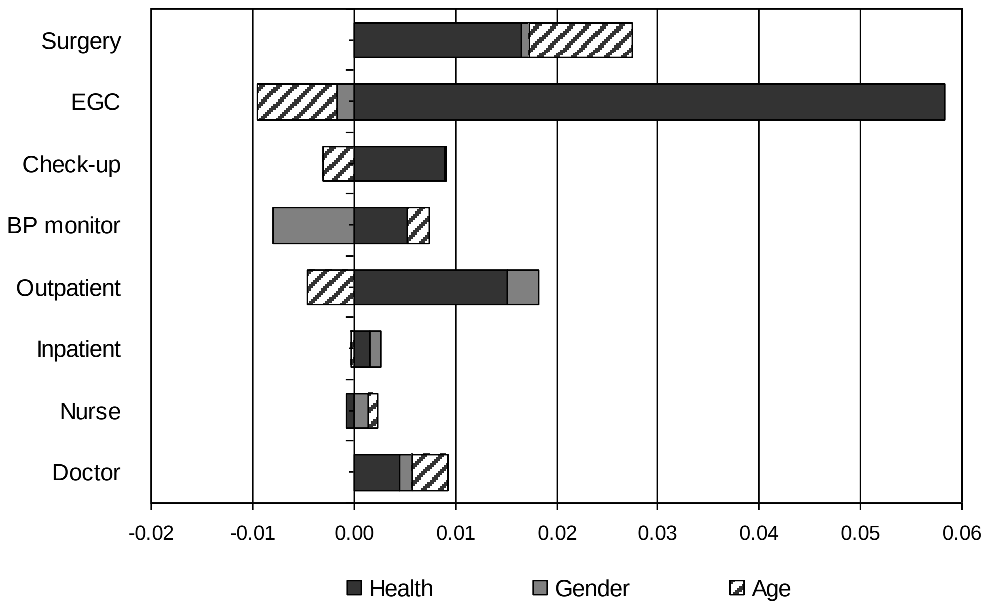
The contribution of the CVD-related need variable is relatively large and significant in every case, suggesting that most of the pro-poor inequalities in actual health care utilisation are explained by the higher needs among poorer groups. The sum of the contribution of all the need variables represented by the dark area in Figure 5.3 illustrates the large size of the contribution of these variables to inequalities in health care use. The inequality that remains after subtracting the effect of the need variables reflects horizontal inequity. Income itself significantly contributes to the extent of estimated pro-rich horizontal inequity in the case outpatient visits and ECG test, while part of the pro-rich horizontal inequity found in the case of inpatient and outpatient visit is due to the contribution of education. The contributions of ethnicity to inequalities in doctor and nurse visit utilisation make the estimates more pro-poor. Being married significantly contributes towards more pro-rich estimates in the case of practice nurse consultations, regular check-ups and ECG tests. In some cases, a large fraction of the inequalities in health care utilisation remains unexplained as illustrated by the size of the contribution of the residual term, especially in the case of practice nurse visits and inpatient stays[15].

Figure 5.4. Contributions to vertical inequity in health care utilisation

Target effect based on the richest 50% subsample



Target effect based on subsample educated to degree level



Note: Decomposition based on linear approximation using average marginal effects from a probit regression.

[15] However, note that the residual factors include both a prediction error and an error generated by the linear approximation to obtain the marginal effects (van Doorslaer *et al*., 2004). Therefore, in a non-linear setting it is difficult to estimate the fraction of the error contribution that is due to unmeasured factors.

When decomposing the differences in the contributions of the need variables across the full sample and the target groups in order to investigate the sources of vertical inequity, we find that the main contributor factor in most types of use arise from the divergence between the estimated and the target effects of the CVD-related health index, followed (and for some types of use, surpassed) by the age indicators contribution; and, to a small extent, the differences in the contribution of gender (see Figure 5.4).

5.5. Discussion and implications for further work

In this chapter we have explored income-related inequity in health care utilisation for individuals reporting CVD, emphasising and illustrating the importance of assessing vertical, as well as horizontal, inequity. We found that concentrating solely on the horizontal inequity assessment offers only a partial view of the extent of income-related inequity and that including vertical inequity estimates may lead us to draw different conclusions about the nature and extent of income-related inequity in health service use.

There is variation in the direction of horizontal inequity (pro-rich/pro-poor) and its magnitude, depending on the type of use considered. Based on our target groups, we show significant pro-rich vertical inequity for the majority of types of use and target groups, suggesting that high-need CVD patients are not being properly prioritised. On average, sicker individuals do not receive as much care as they ought to compared with individuals with better health status. Since high levels of needs tend to be concentrated among the poor, the difference between need-predicted and target use benefits the rich.

Accounting for vertical inequity may generally tend to affect the inequity indices towards relatively more pro-rich estimates. The reasons being that we might expect systematic unmet needs for health care in some groups of the population with a corresponding downward biased estimated coefficient of the need variables, or it might be that the health care system is not being ‘responsive’ enough to the health care needs of a society. In any case, the appropriate magnitude of the effect of the need variable would be stronger than the effect recovered from the regression analysis. This suggests that an allocation based on the appropriate effect of the need variables would allocate more health care use to individuals in higher levels of need. As individuals in high levels of needs tend to be concentrated on the poorer groups of the population, the difference between the need-predicted allocation and the target allocation is likely to benefit those with higher income. This may not necessarily be always the case as target allocations of particular types of care might allocate less health care to relatively sicker individuals than otherwise estimated, on the basis that, for instance, these individuals ought to receive treatment in different health care settings, such as more specialised care.

In terms of our total inequity estimates, nurse visits, blood pressure monitoring and regular heart check-ups were found to be equally distributed across income groups, while outpatient visits, ECG tests and heart surgery are disproportionately concentrated among the rich. The evidence is more ambiguous for doctor visits and inpatient stays; the total inequity estimates are either non-significant or show a pro-rich concentration, depending on the target group used to measure vertical inequity. Note that our utilisation measures include both NHS and private contacts, so the pro-rich concentration of specialist visits (outpatient visits, ECG tests) and heart surgery may be due to the private consumption of these services by the rich; this is consistent with the finding that privately funded provision of coronary revascularisation surgery is negatively correlated with area deprivation (Mindell *et al*., 2008). These results might also provide some evidence of a barrier for those with lower incomes to access secondary care within the NHS. As GPs in England act as 'gatekeepers' of the health care system, our findings may reflect the fact that richer individuals may be more likely to request specialist care while poor individuals may not be as effective in advocating for their own needs (van Doorslaer *et al*., 2006). These findings are consistent with previous evidence (e.g. see review by Dixon *et al.*, 2007). The authors of this review discuss some explanations for this phenomenon. They conclude that '*a major reason for the inequity in use of specialised care within the NHS may be that the better off have a louder voice than the less well off – a 'voice' that is more likely to be heard, understood and, indeed, even empathised with, by the professionals concerned'.*

This study has a number of limitations. First, a feature of the HSE data is that only individuals reporting having a history on any CVD condition (stroke, angina, myocardial infarction or heart attack, diabetes, high blood pressure, heart murmur, irregular heart rhythm or 'other' heart problem) were subsequently asked about their utilisation of health services. This may be a limitation in the analysis as reporting a CVD condition may depend on having been seen by a doctor and thus our sample might reflect a higher propensity to consult health professionals (for diagnosis and/or treatment) than the general population with CVD. If there are unobserved factors that influence the probability of reporting CVD conditions which also influence the utilisation of health services, our estimates could be affected from sample selection bias. We base our analysis and conclusions on inequity among individuals reporting CVD conditions, as we do not observed health care utilisation of those who are not aware or did not report to have CVD. This is a common limitation of analyses that model health care utilisation and rely on reported health measures. We undertook some supplementary work investigating this issue using some additional information available in the HSE. We try to identify individuals with CVD who are unaware of it using information provided in the nurse visit as well as their answers to CVD-related symptom-based problems. We conducted sample selection models and found no evidence of sample selection bias in our results. This is presented and explained in more detail in Appendix 5.7. An additional limitation related with the above issue is that there may be reverse causality between health care utilisation and health in the case that health care use had an impact on the actual or reported individual health status. This is because although most of the indicators of health status are referred to current health, some of the utilisation measures are defined as use in the past, such as in the previous two weeks or twelve months. However, note that in our data most of the health indicators of CVD-related health are generally related to chronic or long-lasting diseases such as diabetes, high blood pressure, angina, etc., and thus this issue is less likely to affect our analyses. The sign of the potential bias on the estimated coefficients and the equity estimators as based upon those is also unclear. In the case that health care utilisation has a positive effect on individual health, the impact of the health indicators on use would be underestimated as those who are heavy users of care would have better health. However, those who are in contact with health services may be more aware of their conditions and report worse levels of health status. In that case, the impact of poor health on use would be overestimated in our data. A potential solution in the context of longitudinal data would be to use lagged measures of health in the health care utilisation equations which avoid the problem of reverse causality. However, these measures commonly refer to health status in the previous year and thus raise the question of how relevant these measures are with respect to utilisation in, for instance, the previous fortnight.

A second limitation of the data is that the HSE does not contain detailed information on utilisation; it is measured crudely using binary variables measuring whether or not a respondent had a particular type of use; no account is made of the quality of those contacts. Moreover, it is not possible to differentiate between elective admission/appointments and emergency admission/casualty attendance for inpatient/outpatient service data. In the context of CVD, A&E attendances and emergency admissions are considered avoidable with good management and treatment, and are thus viewed as a bad outcome. Therefore, if higher rates of these types of contacts were concentrated among poorer individuals that may be interpreted as pro-rich inequities. If that was the case, our estimates of pro-rich inequity in inpatient and outpatient visits would be an underestimation. Third, given the nature of our data and the statistical methods used we cannot draw conclusions about the causal effect of some the covariates on health care utilisation.

Finally, estimating the appropriate effect of the need variables on use, required for analyses of vertical inequity, is far from straightforward. We have based our analyses on target groups which we believe are less likely to have vertical inequity in use. Even in countries with universal coverage, more affluent and well-educated individuals have been found in the literature to be less likely to suffer from unmet health care needs. The reason might be that these groups may experience different marginal utilities of health care consumption as compared with relatively more deprived individuals (Le Grand, 1978). Individuals in higher socioeconomic groups may need less time to access health care (e.g., with better transport and medical facilities) and are less likely to lose income for the time spent consuming health care. Additionally, the marginal valuation of the benefit of health care may be higher if they perceive health care as contributing to their improvement in health. Under these assumptions, we hypothesise that better-off individuals are more willing and able to seek health care treatment when they have an actual need which is corroborated by the findings of a more stepper effect of the need variables among our target groups. However, under any of these target groups, the allocation may still fall short of meeting the needs of the population, providing a level of health care that is not commensurate with the level of needs of the individuals; or it may be the case that the target allocations are ‘overmeeting’ the need of the population by allocating more resources to high need individuals than they actually require[16]. Therefore, while we offer evidence to support our approach, the choice target remains unavoidably subjective.

Finally, we have focused on *income-related* inequity in the provision of health care for individuals with CVD. While in the case of horizontal inequity the income-related

[16] Note that the latter is different from the issue that better-off individuals may, on average, use more health care at any level of needs (which would be captured by the effect of the income or education variables in the utilisation models), but it rather focuses on whether the relative use of health care at different level of needs is appropriate.

inequity analysis is an obvious choice, it is less clear that this is appropriate for the analysis of vertical inequity: income-related vertical inequity is a partial measure of vertical inequity caused by the inappropriate effect of needs, and the concentration of needs in low income groups. We will undertake further work to relax the condition that vertical inequity strictly depends on the relationship between needs and the socioeconomic measure. We propose an extension to the methodology suggested by Sutton, 2002 which it is presented and illustrated in the following chapter.

CHAPTER 6

Extending the measurement of vertical equity in health care delivery – emphasising the need dimension

6.1. Introduction

The measurement of socioeconomic-related inequity including both horizontal and vertical aspects was illustrated in the previous chapter using the most comprehensive methodology found in the literature. However, as highlighted in the literature review in Chapter 4, this methodology, as it has been proposed in the literature, only takes into account the socioeconomic dimension of vertical equity.

The main aim of this chapter is to propose and illustrate an extension to this measure of vertical equity that fully accounts for the variation in needs in a population. This is accomplished by computing the vertical equity estimate using concentration indices with respect to the need rank rather than the socioeconomic rank. The methodology is illustrated and compared with the socioeconomic-related inequity measures computed in the previous chapter using the same data, i.e. 2003 and 2006 rounds of the Health Survey for England (HSE) on cardiovascular disease (CVD)-related health care utilisation of adults with CVD.

The chapter is structured as follows; the next section highlights the limitation of focussing solely on the socioeconomic dimension in the measurement of vertical inequity and presents the methodological extension to quantify vertical inequity with respect to the need distribution. The implications for the analysis of horizontal inequity when using the need indicator as the ranking variable are also drawn. In the following section, we present the results and the comparisons between the income-related and need-related indices of inequity. Finally, we discuss the interpretation and the appropriateness of the different approaches for the measurement of inequity in health care delivery.

6.2. Methodology - extending the measurement of vertical inequity

6.2.1. Illustrating the partial assessment obtained by focusing on socioeconomic-related vertical equity

We aim in this section to develop an estimate of vertical equity that fully accounts for the unequal needs that exist in a population. We build on the estimate proposed by Sutton, 2002, but we relax the condition that vertical equity strictly depends on the relationship between needs and the socioeconomic measure.

It is worth noting that some analysts would not see the limitation of the analysis to the socioeconomic dimension as a problem, as they might argue that, as in the case of inequalities in health, what it is worrying is not that inequalities exists, but that they mirror inequalities in socioeconomic status (Wilkinson, 1986). Therefore, following this argument, an analogous question with respect to vertical inequities in health care use is whether individuals with different needs do not receive appropriately different treatment, and the extent to which this mirrors inequalities in socioeconomic status. In that case, the measurement of inequity should focus on the socioeconomic dimension of that inequity by exploring systematic variation across socioeconomic groups in the allocation of the variable of interest. That is the current practice in the analysis of horizontal inequity, where the focus is in most cases to identify whether individuals with equal needs do not receive the same treatment due to differences in their socioeconomic status. We believe this approach to be an obvious and appropriate choice in the case of horizontal inequity analysis, whose aim is to identify systematic variations in treatment provided to those with equal needs. However, in the context of vertical inequity this approach is rather restrictive. Vertical inequity arises when health care delivery is not allocated appropriately according to differences in needs. This definition therefore does not require inequity to be measured with respect to a socioeconomic dimension, but in fact emphasises the need dimension. We recognise though at the outset of this chapter that the choice between the socioeconomic estimate of vertical inequity and the estimate of vertical inequity proposed in this chapter would depend on the research question at hand. Nevertheless, we believe our proposed measure to be more in line with how vertical equity is generally defined in the literature.

To illustrate, we start by focussing on the case of the inclusion of one need index in the utilisation equation. The implications of adding more need variables are discussed next. We can write the index of vertical inequity proposed by Sutton, 2002 using the decomposition property of the concentration index, as the difference between the contribution of needs under the estimated effect of the need variable and the contribution of needs under the appropriate, or target, effect of the need variable,

$$VI^{I} = (\hat{\beta} - \beta^{*})\frac{\overline{N}}{\overline{q}} CI_{N}^{I} \tag{6.1}$$

Where $\overline{q}$ is the mean health care consumption; $\overline{N}$ is the mean of the need variable, $\hat{\beta}$ and β^{*} are the estimated and the target effect of the need variable, respectively; and CI_{N}^{I} stands for the concentration coefficient of needs with respect to the SES ranking variable, usually income, that we denote *I*[17].

In Equation (6.1) it becomes evident that the measurement of vertical inequity using this approach is defined as the difference between the estimated and the target effect of the need variable, times the concentration coefficient of the need variable with respect to SES (scaled by the ratio of the average need and health care use values). Therefore, in the case that the concentration index of the need variable with respect to socioeconomic status (which measures the socioeconomic-related inequalities in needs) was close to zero, the estimate of vertical equity would tend to zero. This would be independent of the size of the difference between the actual and the target effect of needs on use, i.e. the source of vertical inequity. Therefore, this approach is only capable of identifying vertical equity to the extent to which needs are correlated with socioeconomic status and it would not be capable to account for sources of vertical inequity that are uncorrelated or weakly related to socioeconomic status. This means that even if individuals with different levels of needs do not receive appropriately unequal treatment but they are equally distributed in the SES distribution, the measure of SES-related vertical inequity would not be able to pick the failure to provide vertically equitable health care. This measure is thus capturing what Gravelle *et al.*, 2006 defined as the consequence of vertical inequity across the socioeconomic distribution.

6.2.2. Measuring vertical inequity with respect to the need rank

In order to develop a measurement of vertical equity which is not restricted to the socioeconomic dimension we need to further extend the vertical equity estimate. The

[17] Note that from hereafter, we include a superscript to the CI to denote whether the rank is with respect to the SES measure, *I*, or with respect to the need measure, *N*.

principle of vertical equity relates to the allocation provided across different need groups, and therefore we believe the need dimension becomes the most relevant option for the measurement of the extent to which individuals with different needs do not receive appropriately different treatment. We propose thus to focus on the need dimension and measure vertical equity as the difference between the need-predicted and the target health care allocation with respect to the need distribution. The analysis would be analogous to the measure of socioeconomic-related inequity, but in our proposed approach the concentration curves of health care allocation are drawn by ranking individuals according to their need level for health care. The need-related vertical equity estimate is given by,

$$VI^{N} = 2 * \int [CC_{target} - CC_{need-predicted}] = CI_{\hat{q}}^{N} - CI_{q^{*}}^{N} \qquad (6.2)$$

Note that in this case, and similarly to the case of socioeconomic-related inequity when the ranking variable is often chosen to be income, it would be necessary a measure of needs that provides variation within the population in order to rank individuals accordingly. The vertical equity estimate would then be measured with respect to this need variable that can be derived as a composite index of different need factors such as age, gender, morbidity and severity indicators as shown in the previous chapter when deriving a CVD-related need index. The range of values of the VI^N is the same than that of the VI^I, i.e. between -1 and +1. In the case of the need-related estimate, a positive (negative) value indicates that there is vertical inequity favouring the healthier (sicker).

Using the decomposition property and analogous to Equation (6.1), the estimate of need-related vertical equity with respect to the need variable could be written as,

$$VI^{N} = \left(\hat{\beta} - \beta^{*}\right)\frac{\overline{N}}{\overline{q}} Gini^{N} \qquad (6.3)$$

The concentration index of the need variable with respect to the need distribution is equivalent to the Gini index of needs, or the measure of overall inequalities in needs in a population as defined in Chapter 2. Therefore, the estimate of need-related vertical equity would be sensitive to how needs are distributed in the population under study, and in the case that everyone had similar level of needs (Gini coefficient close to zero) the estimate of vertical inequity would legitimately tend to zero, suggesting that if there are not 'unequal' individuals in the population there is not vertical inequity. The estimate of vertical inequity becomes larger as the Gini coefficient increases, which means that the larger the inequality in the need distribution, the larger the degree of vertical inequity, all else equal.

This measure of need-related vertical inequity would necessarily be equal or larger than the socioeconomic-related vertical inequity. The intuition is given by the fact that the measure of need-related vertical equity is capable of accounting for the full variation of needs in the population, while the socioeconomic-related vertical equity only captures that extent to which need varies across the income distribution, which must be smaller than or equal to the measure of overall inequalities in needs. To illustrate, note that the ratio between the need-related and the socioeconomic-related vertical inequity is given by the ratio between the Gini coefficient of needs and the concentration index of needs with respect to socioeconomic status,

$$\frac{VI^N}{VI^I} = \frac{\left(\hat{\beta} - \beta^*\right) * \frac{\overline{N}}{\overline{q}} * Gini^N}{\left(\hat{\beta} - \beta^*\right) * \frac{\overline{N}}{\overline{q}} * CI_N^I} = \frac{Gini^N}{CI_N^I} \tag{6.4}$$

For the computation of the concentration index, the following convenient formula is generally applied and given by,

$$CI_N^I = \frac{2}{\overline{N}} \operatorname{cov}(N, r_I) \tag{6.5}$$

Where, r_I denotes the rank variable in the socioeconomic distribution. The analogous formula for the Gini coefficient, where r_N stands for the rank in the need distribution, is as follows,

$$Gini^N = \frac{2}{\overline{N}} \operatorname{cov}(N, r_N) \tag{6.6}$$

Therefore, the argument in Equation (6.4) becomes,

$$\frac{VI^N}{VI^I} = \frac{Gini^N}{CI_N^I} = \left|\frac{\mathrm{cov}(N, r_N)}{\mathrm{cov}(N, r_I)}\right| \geq 1 \qquad (6.7)$$

The covariance between need and the need rank is necessarily larger than the covariance between need and the socioeconomic rank as the former implies ranking individuals according to the same variable that is used to compute the covariance; only in the case that socioeconomic status and needs were perfectly correlated, both estimates would be the same (Wagstaff & van Doorslaer, 2004). Thus, the higher the re-ranking needed to move from the SES to the needs distribution, the larger the difference between the Gini index and concentration coefficient of needs with respect to SES, and therefore the larger the difference between the need-related and the SES-related vertical inequity estimates. In the unlikely case that needs and SES were perfectly negatively correlated the estimates would take opposite signs.

This result is likely to hold when more need indicators are included in the utilisation equation. In the case that a set of *k* need indicators are included in the analysis, the index of SES-related vertical inequity is given by,

$$VI^I = \sum_k (\hat{\beta}_k - \beta_k^*) \frac{\overline{N}_k}{\overline{q}} CI_k^I \qquad (6.8)$$

If among the *k* need indicators, a measure of health *H* is used as the ranking variable in the analysis of need-related vertical inequity the index of need-related VI is defined as,

$$VI^H = \sum_k (\hat{\beta}_k - \beta_k^*) \frac{\overline{N}_k}{\overline{q}} CI_k^H \qquad (6.9)$$

The difference in the contribution of the need variable which is used as the ranking variable can be disentangled from the analogous components of the other need indicators,

$$VI^H = \left(\hat{\beta} - \beta^*\right)\frac{\overline{H}}{\overline{q}} Gini^H + \sum_{k-1}\left(\hat{\beta}_k - \beta_k^*\right)\frac{\overline{N}_k}{\overline{q}} CI_k^H \qquad (6.10)$$

In the case of the SES-related VI using a measure of socioeconomic status *I* as the ranking variable, the index becomes,

$$VI^{I} = \left(\hat{\beta} - \beta^{*}\right)\frac{\overline{H}}{\overline{q}}CI_{H}^{I} + \sum_{k-1}\left(\hat{\beta}_{k} - \beta_{k}^{*}\right)\frac{\overline{N}_{k}}{\overline{q}}CI_{k}^{I} \qquad (6.11)$$

Therefore, the first component of the right-hand side of Equation (6.10) and (6.11) are equivalent to the case where only one need indicator is included in the analysis, and therefore hold the same relationship as explain above. The second component is the sum of the differences between the contribution of the other need indicators under the estimated and under the target effect of these need variables. The difference across the need-related and the SES-related approach would therefore also depend on the difference between the concentrations of the other need indicators with respect to the health variable and with respect to the income variable. The other need indicators included in the model, such as measures of age, morbidity, severity, etc., are likely to be more highly correlated with the health variable than with the socioeconomic measure. Therefore, the estimate of need-related vertical equity would still be expected to show a larger degree of inequity, in absolute terms, than the corresponding socioeconomic vertical equity estimates.

6.2.3. Implications for the analysis of horizontal inequity

The inclusion of the need dimension in the analysis of vertical equity allows us to measure vertical inequity across individuals with different needs fully, and by focusing on the socioeconomic dimension as proposed by Sutton, 2002, we can measure the fraction of that inequity that have consequences for the allocation across different income groups. In the case of horizontal inequity, we consider the standard approach of measuring horizontal inequity with respect to the socioeconomic dimension an obvious and appropriate choice. But in addition to exploring that, the incorporation of the need dimension to the equity analysis allows us to explore the distributional consequences of the effect of the non-need variables on health care use across need groups.

To illustrate, we exploit again the decomposition property of the CI. Using the decomposition approach, the estimate of socioeconomic-related horizontal inequity is defined as the inequality in health care utilisation that remains after subtracting the contribution of the need variables to the CI. The estimate of socioeconomic horizontal inequity where Y_j is a set of *j* non-need variables (and *I* is the ranking socioeconomic variable contained in Y_j) is then defined as,

$$HI^{I} = CI_{q}^{I} - \left(\frac{\hat{\beta}\ \overline{N}}{\overline{q}} CI_{N}^{I} \right) = \left(\sum_{j} \frac{\hat{\delta}_{j}\overline{Y}_{j}}{\overline{q}} CI_{Y}^{I} \right) + \left(\frac{GCI_{\varepsilon}^{I}}{\overline{q}} \right) \tag{6.12}$$

This estimate assumes that the variation in utilisation across income groups that remains after extracting the contribution of the need indicators is due to non-need factors, and it is therefore considered to be horizontally inequitable. This estimate has been labelled the 'conventional horizontal inequity index' by Bago d'Uva *et al.,* 2009. The authors of this paper proposed a more 'conservative horizontal inequity index' that excludes the contribution of the residual, on the basis that the error term may be picking up unobserved need factors. Taking the last definition, the index of horizontal inequity equals the contribution of the non-need variables to the socioeconomic inequalities in health care use.

The contribution of the non-need indicators can be divided into the contribution of the variable used as ranking variable for the computation of the CIs, denoted by *I*, and the contribution of the remaining non-need indicators. The concentration index of income with respect to the income variable is equivalent to the Gini coefficient of income inequality; the horizontal inequity estimate can thus be written as,

$$HI^{I} = \frac{\hat{\delta}\ \bar{I}}{\bar{q}} Gini^{I} + \sum_{j-1} \frac{\hat{\delta}_{j}\overline{Y}_{j}}{\bar{q}}\ CI_{j}^{I} + \frac{GCI_{\varepsilon}^{I}}{\bar{q}} \tag{6.13}$$

The estimate of the horizontal inequity estimate with respect to the need ranking is considered next. This need-related horizontal inequity estimate captures the consequences of the effect of the non-need indicators on the allocation of health care utilisation across need groups. For instance, if high need groups are concentrated on the poorer part of the distribution, then a positive effect of income on use implies that sicker individuals receive less health care use than they ought to. We can measure this by computing the horizontal inequity estimate with respect to the need rank, which, using the formula developed above, can be written as,

$$HI^N = \frac{\hat{\delta}\ \bar{I}}{\bar{q}} CI_I^N + \sum_{j-1} \frac{\hat{\delta}_j \bar{Y}_j}{\bar{q}} CI_j^N + \frac{GCI_\varepsilon^N}{\bar{q}} \tag{6.14}$$

Analogous to the results for vertical equity, the difference between the first components of the right-hand side of Equation (6.13) and (6.14) is given by the difference between the overall income inequalities and inequalities in income which have a need gradient. The latter are necessarily smaller or equal than the overall inequalities in income. With respect to the second component of the right-hand side of each equation, it is likely that the other non-need indicators, such as education, ethnicity, etc. are more strongly correlated with the SES variable than with the need indicator, making the sum of these contributions larger (in absolute terms) in the case of the SES-related indices. However this might not necessarily be the case. Moreover, if one were to include the contribution of the error term as part of the measure of horizontal inequity, the correlation of the unexplained variation in health care use might be stronger with respect to the need factor than with respect to the SES variable, making this component larger in the need-related horizontal inequity estimate. Therefore, the difference in the size between the SES-related and the need-related horizontal inequity estimates remains ambiguous.

6.2.4. Measuring total inequity with respect to the need rank

The indices of vertical and horizontal inequity with respect to the need rank can be combined, in a similar manner to those computed with respect to the income rank, to derived the need-related total inequity estimates. Alternatively, the index can be computed directly as the difference between the CI of actual allocation and the CI of the target allocation with respect to the need rank.

$$TI^N = 2 * \int [CC_{target} - CC_{actual}] = CI_q^N - CI_{q^*}^N \tag{6.15}$$

The magnitude of this index in comparison with the SES-related total inequity estimate is not obvious as it would depend on the differences between the vertical and horizontal inequity aspects as explained above. The index lies between -1 and +1, with positive (negative) values indicating that health care is not appropriately distributed according to needs, and that the allocation disproportionally favours the healthy (sick).

6.3. Empirical results

The results shown in this chapter are based on the same data and use the health, income and health care utilisation regression model results as presented in the previous chapter, but compare the measures of vertical, horizontal and total inequity when the concentration indices are computed with respect to the need rank with those computed with respect to the income rank. For each of the eight types of health care utilisation measures investigated in this study, we present the previously computed indices of income-related vertical, horizontal and total inequity next to the newly derived indices of need-related vertical, horizontal and total inequity for ease of comparison.

The primary outcomes of these analyses are the comparisons between the income-related and the need-related vertical inequity indices, but the estimates for horizontal and total inequity using both the income and the need rank approach are also presented. In addition, the indices of horizontal inequity are computed using two different definitions as explained above, i.e. the ‘conventional’ and the ‘conservative’ horizontal inequity measures, the difference between the two being that the latter excludes the contribution of the error term in the quantification of horizontal inequity.

Tables 6.1 and 6.2 summarise these results. For most types of use and target groups the indices of vertical inequity (VI) are positive, indicating pro-rich and pro-healthy vertical inequity in the income-related and need-related inequity estimates, respectively. The two exceptions are the inpatient visit and the probability of receiving blood pressure monitoring when the target group is based on the richest 50%, but none of these estimates are significant. When vertical equity is measured with respect to the need distribution, the extent of vertical inequity is much larger. This finding shows that the difference between the need-predicted and the target allocation of health care is proportionally larger amongst those in higher needs, and that this gap is substantially larger than when only the socioeconomic dimension is taken into account. Therefore, there is more vertical inequity with respect to needs than with respect to income. As in the case of income-related VI, the indices of need-related VI are larger when the education target group is used to estimate the appropriate effect of the need indicator, and are statistically significant for doctor visits, outpatient attendances, regular check-ups, ECG tests and inpatient stays (the last one is only weakly significant). Using the richer 50% target group, there is significant pro-healthy vertical inequity in the probability of having ECG test and heart surgery.

Table 6.1. Estimates of need-related and SES-related inequity in CVD-related health care utilisation (doctor, nurse, inpatient, outpatient visit)

	Doctor visit				Nurse visit			
Equity estimates*	**Income rank**		**Need rank**		**Income rank**		**Need rank**	
	CI	**CI/SE**	**CI**	**CI/SE**	**CI**	**CI/SE**	**CI**	**CI/SE**
Vertical equity								
Richer 50%	0.0062	1.42	0.0177	1.49	0.0062	1.64	0.0106	1.10
Having degree	0.0219	2.36	0.0497	2.15	0.0137	1.39	0.0252	1.09
Horizontal equity								
Conventional	0.0014	0.26	-0.0082	-1.43	-0.0129	-2.65	-0.0101	-2.08
Conservative	0.0010	0.21	0.0014	0.93	-0.0065	-1.91	-0.0026	-2.04
Total equity								
Conventional								
Richest 50%	0.0076	0.92	0.0095	0.78	-0.0067	-0.99	0.0005	0.04
Having degree	0.0233	1.95	0.0414	1.76	0.0007	0.06	0.0151	0.64
Conservative								
Richer 50%	0.0072	1.17	0.0192	1.57	-0.0003	-0.05	0.0080	0.81
Having degree	0.0229	2.12	0.0511	2.17	0.0071	0.65	0.0225	1.01

	Inpatient visit				Outpatient visit			
Equity estimates*	**Income rank**		**Need rank**		**Income rank**		**Need rank**	
	CI	**CI/SE**	**CI**	**CI/SE**	**CI**	**CI/SE**	**CI**	**CI/SE**
Vertical equity								
Richer 50%	-0.0005	-0.13	-0.0038	-0.41	0.0056	1.25	0.0076	0.54
Having degree	0.0148	1.82	0.0407	1.82	0.0282	2.70	0.0778	2.49
Horizontal equity								
Conventional	0.0015	0.38	-0.0047	-1.02	0.0239	3.53	-0.0124	-1.84
Conservative	0.0047	1.66	0.0023	2.28	0.0223	3.38	0.0089	4.04
Total equity								
Conventional								
Richest 50%	0.0018	0.33	-0.0085	-0.89	0.0295	3.14	-0.0048	-0.33
Having degree	0.0163	1.73	0.0360	1.59	0.0521	3.90	0.0654	2.08
Conservative								
Richer 50%	0.0042	0.85	-0.0016	-0.16	0.0279	3.33	0.0165	1.15
Having degree	0.0195	2.22	0.0430	1.89	0.0505	4.02	0.0867	2.75

Note: CI = Concentration index; SE = Standard Error; *SE computed using bootstrapping techniques.

Table 6.2. Estimates of need-related and SES-related inequity in CVD-related health care utilisation (monitor BP, Check-ups, ECG test and surgery)

	Monitor BP				Regular check-ups			
Equity estimates*	Income rank		Need rank		Income rank		Need rank	
	CI	CI/SE	CI	CI/SE	CI	CI/SE	CI	CI/SE
Vertical equity								
Richer 50%	-0.0095	-1.24	-0.0102	-0.58	0.0047	0.53	0.0186	0.87
Having degree	0.0091	0.45	0.0398	0.93	0.0445	1.70	0.1107	2.16
Horizontal equity								
Conventional	-0.0150	-1.09	-0.0110	-1.62	-0.0142	-0.87	-0.0361	-2.21
Conservative	-0.0004	-0.04	0.0004	0.09	-0.0136	-1.08	-0.0092	-1.74
Total equity								
Conventional								
Richest 50%	-0.0245	-1.36	-0.0212	-1.15	-0.0095	-0.45	-0.0175	-0.80
Having degree	-0.0059	-0.23	0.0288	0.67	0.0302	0.95	0.0746	1.43
Conservative								
Richer 50%	-0.0099	-0.75	-0.0099	-0.54	-0.0089	-0.58	0.0093	0.43
Having degree	0.0087	0.37	0.0402	0.93	0.0309	1.07	0.1015	1.94
	ECG test				**Surgery**			
Equity estimates*	**Income rank**		**Need rank**		**Income rank**		**Need rank**	
	CI	**CI/SE**	**CI**	**CI/SE**	**CI**	**CI/SE**	**CI**	**CI/SE**
Vertical equity								
Richer 50%	0.0096	2.05	0.0347	2.29	0.0254	3.45	0.0542	2.65
Having degree	0.0287	2.37	0.0886	2.83	0.0350	1.89	0.0751	1.35
Horizontal equity								
Conventional	0.0498	5.73	-0.0230	-2.24	0.0452	3.24	-0.0071	-0.51
Conservative	0.0406	4.93	0.0099	3.52	0.0393	2.88	0.0120	0.00
Total equity								
Conventional								
Richest 50%	0.0594	4.84	0.0117	0.76	0.0706	4.08	0.0661	3.17
Having degree	0.0784	4.47	0.0657	2.11	0.0803	3.29	0.0870	1.55
Conservative								
Richer 50%	0.0502	4.67	0.0445	2.90	0.0647	4.11	0.0471	2.26
Having degree	0.0692	4.61	0.0985	3.17	0.0744	3.23	0.0680	1.21

Note: CI = Concentration index; SE = Standard Error; BP = Blood Pressure; ECG = electrical recording of the heart. *SE computed using bootstrapping techniques.

Moving to the results of horizontal inequity (HI), we first discuss the difference between the ‘conservative’ and ‘conventional’ horizontal inequity estimates computed using the standard income rank approach. Compared with the conventional estimates that incorporate the residual contribution, the conservative estimates are in most cases smaller (in absolute terms) indicating a smaller degree of horizontal inequity (pro rich or pro-poor) than estimated using conventional techniques. However, in every case the ‘conservative’ and ‘conventional’ HI indices have the same sign and therefore provide the same answers to the question of whether there is pro-rich or pro-poor inequity. This was also the result found by Bago d’Uva *et al*., 2009. The special case in our study are inpatient visits, whose estimates of HI become more pro-rich and weakly significant when the contribution of the error term is excluded as compared with the non-significant and considerably smaller conventional HI estimate. These results suggest that the assumption that the contribution of the residual due to the prediction error is attributed to unjustifiable sources of inequity might have implications for the conclusions drawn about the estimated horizontal inequity.

As expected, the relationship between the need-related and the income-related horizontal inequity is not straightforward. The ‘conservative’ estimates suggest a consistent pattern where the HI estimates with respect to income are larger (in absolute terms) than the corresponding need-related HI estimates. However, the comparison across need-related and income-related HI using the ‘conventional’ estimates shows that most indices become more negative when the need dimension is considered. By comparison with the results based on the ‘conservative’ estimates, this finding implies that what is driving the difference between these two types of estimates is that the residual term is more strongly (and negatively) correlated with the health variable than with the income variable, making the need-related HI estimates more negative (i.e. more pro-sick) in every case. Finding that the concentrations of the error term are generally stronger with respect to need factors than with respect to SES factors might provide some support to the assumption that the error terms might mainly pick up unobserved need for health care rather than unjustifiable sources of inequality. This might suggest that the assumption underpinning the conventional approach does not hold.

Taking the ‘conventional’ estimates as the measure of HI, the *total* inequity (TI) estimates that combined vertical and horizontal aspects of inequity shows that there is some evidence of inequity favouring specific need groups of the population. In some cases, an observed equitable total allocation is due to a combination of a pro-sick horizontal inequity and a pro-healthy vertical inequity estimate. Doctor visits, outpatient visits and ECG tests are found to be significantly pro-healthy under the education target group (the first one weakly so), while there is also evidence of heart surgery being more concentrated on healthy groups of the population when the sample of the richest 50% is used to measure the optimal effect of needs. The ‘conservative’ measures of HI lead in most cases to the same TI conclusions. In addition to the pro-healthy inequity found with respect to doctor visit, outpatient visit, ECG test and heart surgery, there is evidence of pro-healthy inequity in inpatient visits and in receiving regular check-ups when individuals with a degree are used to form the target group. When comparing the total inequity estimates between those computed using the need rank and those using the income rank, we find that in most (but not all) cases, the extent of total inequity is larger with respect to needs than with respect to income.

6.4. Discussion

In this chapter we have highlighted the limitation for the measurement of vertical inequity of the most comprehensive approach found in the literature, i.e. the focus solely on the socioeconomic dimension of the vertical inequity. This measure would be appropriate if the interest of the analyst is to quantify the extent to which vertical inequity affects the allocation of health care across income groups. However, if the aim of the analysis is to derive a measure of the extent to which individuals with unequal needs receive appropriately different treatment (as vertical equity has extensively been defined) this analysis would be rather limited, especially if needs and SES are not highly correlated. As shown in this chapter, unless the socioeconomic measure is perfectly correlated with needs, this approach would only be capable to pick up a fraction of the extent to which individuals with different needs do not receive appropriately different treatment across the need distribution.

Therefore, in this chapter we suggest to measure vertical equity with respect to the need dimension in order to fully account for the variation in needs across the population, and not just the extent to which need varies across the income distribution. This measure of vertical equity is necessarily equal or larger than the SES-related vertical inequity estimate when one need measure is used in the utilisation regression analysis, and this is also likely to hold when more need indicators are included as demonstrated in our analyses. The estimate is sensitive to the distribution of needs in the population under analysis. This latter property is crucial for the measurement of vertical equity as it ensures that the index would be larger in a population where individuals are more ‘unequal’ with respect to their needs than in a population where everyone have relatively similar needs.

The extent of vertical inequity was shown to be much larger when the full distribution of needs is taken into account. The difference between these two estimates is mainly driven by the difference between the concentration coefficient of the health variable with respect to income (i.e. the income-related inequalities in health) and the Gini index of health (i.e. the overall inequalities in health), the former found to be around 28% of the latter (see Appendix 6.1). These results are in line with the results found in Chapter 2 where the indices of income-related inequalities in health and overall inequalities in health were computed using HSE data from 1998 until 2006. Previous studies have also found the income-related inequalities in health to be approximately 25% of the overall inequalities in health using different sets of data such as malnutrition amongst Vietnamese children and health utility amongst Canadian adults (Wagstaff & van Doorslaer, 2004). Therefore, similar results on the relationship between need-related and SES-related vertical equity as shown in this study are likely to be found elsewhere.

We also showed the implications for the analysis of horizontal inequity, and found some interesting results with respect to the assumptions commonly applied in the analysis of HI. Firstly, we compared the conventional approach that assumes variations in utilisation due to the error term to be unjustifiable sources of inequity and therefore part of the index of horizontal inequity, with the so-called conservative approach that excludes this element on the basis that might pick up unobserved needs. Some results were found to be sensitive to this assumption. Moreover, we found some evidence suggesting that this residual term may be picking up unobserved need characteristics rather than unjustifiable variations in utilisation, as its correlation was found to be considerably stronger with respect to the need index than with respect to the income variable. This might suggest that the assumption underpinning the conventional approach does not hold, and therefore the estimates using the conservative approach might be preferred. This suggests that similar analyses ought to be conducted in horizontal inequity studies in order to explore the validity of this assumption.

Focusing on the total inequity results (HI + VI), we found evidence of total inequity favouring the healthy in a number of types of health care utilisation. These results suggest that the high needs of some individuals are being ‘squeezed’ by the less important demands of others for these particular health services (Sutton, 2002). Furthermore, for some of the health care services that were found to be equally distributed with regards to the TI estimates, the result were derived from a combination of a pro-sick HI and a pro-healthy VI, and therefore highlights the importance of measuring these two aspects separately. For instance, individuals with lower income have a higher probability of having a nurse visit, which generates a pro-sick estimate of HI; however, individuals with higher needs do not have appropriately higher use of this service leading to a pro-healthy VI estimate. In conjunction, these two factors generate an allocation of this service that appears to be equally distributed across need groups.

We have argued that the need dimension is more appropriate to fully capture vertical inequity; but we considered the socioeconomic dimension to be an appropriate choice for the analysis of horizontal inequity, given that the focus of horizontal inequity analyses is on identifying systematic variations in the provision of health care to individuals with equal needs. Therefore, a full measure of inequity in a system might ideally combine the need-related vertical inequity and the socioeconomic-related horizontal inequity estimates. However, these measures are derived using different ranking variables for the computation of the indices, and thus they cannot simply be added together. Separately measuring both horizontal and vertical inequity with respect to the need dimension and with respect to the SES dimension allows us though to appropriately measure both vertical and horizontal inequity aspects and the consequences that each of them has on the population groups identified by the other. This condition highlighted by Gravelle, *et al*., 2006 when considering the challenges in the quantification of inequity in health care delivery, was not appropriately met by any of the methodologies used to date in the literature.

With respect to the appropriate dimension for the total inequity estimation (horizontal plus vertical), the choice will depend on the research question at hand. If the aim of the analyst is to monitor whether individuals who need health care the most are receiving the treatment they ought to, however poor or rich they happen to be, the need dimension would capture the extent to which the allocation of health care is or is not equitable across need groups. The socioeconomic dimension in health care equity analysis will provide the answer to whether individuals in particular income groups are being discriminated in the allocation of health care. We believe both questions to be of high relevance and therefore, in this chapter we have tried and present the methodology for the analysis of these two questions and the comparison across them.

As a brief summary of the findings with respect to vertical inequity of this thesis so far, we have shown in Chapter 5 that focusing solely on the socioeconomic-related horizontal inequity analysis offers only a partial view of the inequity across income groups in a system. Therefore the incorporation of the income-related vertical inequity is necessarily in order to draw any conclusion about inequities in the provision of health care across the income distribution. Furthermore, in this chapter we have shown that focusing only on the socioeconomic dimension of vertical inequity offers a partial assessment of the extent to which individuals with unequal needs do not receive appropriately unequal treatment. We have thus proposed to measure vertical inequity with respect to variations in health care provision across need groups.

In the next chapter we will employ the techniques developed in this thesis to assess horizontal and vertical inequity in area level allocations of health care expenditure across Primary Care Trusts in England. Ensuring equity in the distribution of resources across geographical areas in England is a major policy objective. We will test the methodology proposed in this thesis for the analysis of vertical and horizontal inequity, which have been illustrated so far using individual level information, to the context of measuring inequity across area level observations.

CHAPTER 7

Vertical and horizontal inequity in area level allocations of cancer spending in England

7.1. Introduction

Our investigation of equity in the delivery of health care undertaken in this thesis so far has focused on analyses using individual level data. While inequities at the individual level in health care utilisation have been the focus of extensive empirical analysis, variations in area level health care spending are also a major concern.

The major aim of promoting equity in the English NHS becomes obvious in many Government documents and academic studies. Since mid-1970s, attention to inequalities in expenditure between administrative areas has become even more explicit, with a resource allocation formula designed to eliminate such inequalities. The Advisory Committee on Resource Allocation (ACRA) and it's Technical Advisory Group (TAG) oversee the development of the NHS weighted capitation formula used to inform Primary Care Trusts (PCTs) revenue allocations in England on the basis of explicit equity objectives. Currently, ACRA's objective is to develop a robust, evidence based formula for revenue allocations which i) ensures equal opportunity of access to health care for people at equal risk; and ii) contributes to the reduction in avoidable health inequalities.

However, there continues to be widespread concern about the variations in the magnitude of spending in health care across PCTs in England, which have been found to be particularly large in mental health, cancer and circulatory diseases (Appleby & Gregory, 2008). Measuring inequities in area level allocations is not straightforward. A common issue when analysing inequities in area level health care delivery is that measures of needs are often very crude. In this chapter we analyse vertical inequity and horizontal inequity in area level allocations of expenditure across Primary Care Trusts (PCTs) in England for one disease programme – cancer.

Similar to the individual level analyses undertaken in Chapter 5 and 6 in this thesis, the focus on disease-specific spending allows us to use disease-specific need measures that are more likely to capture need for disease-specific health care resources (van Doorslaer *et al.*, 2006). The rationale for the focus on cancer in the analysis conducted in this chapter is that it was the disease area with the most comprehensive information on expenditure, prevalence, and severity available for the longest period of data. Furthermore, when taking a disease-specific approach, the need for the disease area to represent a disease of high burden in terms of patients and cost was highlighted in Chapter 6. Cancer is the leading cause of death worldwide (World Health Organization, 2011). Over 250,000 people in England are diagnosed with cancer every year and around 130,000 die from the disease (Department of Health, 2011). According to the Programme Budgeting Data (PBD) analysis of expenditure by disease programme[18], the NHS spent £5.86 billion on cancer in 2009/10 making it the third largest area of programme expenditure. Nonetheless, we recognise that while our methods are generalizable, the results for cancer may not be generalizable to other diseases; we discuss why this may be the case in the discussion section.

The aim of this chapter is to measure the extent to which areas with larger deprivation and/or areas with larger medical needs are being favoured or disfavoured in the provision of health care. We use information on PCT spending on cancer from 2004/05 to 2008/09 extracted from the Programme Budgeting data. A dataset of PCT variables is assembled from publicly available sources on cancer prevalence and mortality, demographic profiles, deprivation, and health care supply. In addition, we create a cancer-related severity index using information from a household survey. Various econometric specifications are investigated to regress cancer expenditure against the covariates accounting for the longitudinal nature of the data and potential endogeneity. We measure inequity in allocations using the concentration index approach, and identify contributions to inequity using decomposition techniques. To measure horizontal and vertical inequity we use both deprivation and needs as ranking variables using the techniques developed in previous chapters of this thesis but adapted to the context of area level and longitudinal data. To estimate the target effect of the need variables, information from a series of performance indicators is used in order to select subgroups of PCTs more likely to meet the needs of their population more appropriately.

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18 http://www.dh.gov.uk/en/Managingyourorganisation/Financeandplanning/Programmebudgeting/

The chapter is structured as follows, previous evidence on area level inequity in health care are summarised in the next section. The methods section summarises the methodology for the measurement and explanation of inequity indices using longitudinal data. The empirical methods and econometrics models are explained next. The data section summarises the variables used in the regression models. Empirical results from the econometric models, inequity indices and decomposition analyses are then presented; the final section concludes and draws the main implications of our results.

7.2. Previous evidence on area level inequity in health care

Most analyses of inequity in health care allocations at the area level in the literature have focused on variations in utilisation rates of elective surgery across socioeconomic groups. Goddard and Smith, 2001 and Dixon *et al.*, 2007 identified several studies that support the idea that cardiac surgical intervention rates are larger in more affluent areas. In the studies where higher rates were found in more deprived areas, the gradients were thought not to be sufficient to match the socioeconomic differential in mortality. Operation rates for other conditions amenable to surgery, such as arthritis of the hip, have also been found to be lower in more deprived areas (Chaturvedi & Ben-Shlomo, 1995). Cookson *et al.*, 2010 estimated small area associations between two procedures (hip replacement and coronary revascularisation) with area deprivation after controlling for needs and supply indicators. They found a small area deprivation gradient with utilisation rates falling in the most deprived areas for both surgical procedures.

With respect to the work undertaken to review the need component of the resource allocation formulae, the AREA report (Sutton *et al.*, 2002) and the CARAN report (Morris *et al.*, 2007) have found some evidence of underutilisation of health care by ethnic minorities and deprived groups (specifically, those deprived with respect to employment and education).

In the case of cancer service delivery, Goddard's and Smith's review found that screening uptakes rates were lower in areas with higher levels of deprivation, and these findings were supported by a later review from Dixon *et al*., 2007. Cancer patients living in more deprived areas have also been found to be more likely to be diagnosed after an emergency admission, which is a maker of poor outcome (Pollock *et al.*, 1998). In addition, lower chemotherapy rates for colorectal cancer patients have been found for individuals living in more deprived regions (Mclead, 1999). Campbell *et al.*, 2002 found that socio-economic and rurality status of the area of residence have a minor impact on modalities of treatment for colorectal and lung cancer, but do not lead to delays between referral and treatment in Scotland. There is some evidence also from Scotland that suggest no differences in access or treatment for breast cancer between women living in more affluent and deprived areas (Macleod *et al.*, 2000). Therefore, there is evidence of poorer treatment in more deprived areas, but also evidence of equal treatment (Dixon *et al.*, 2007) in cancer health service allocation. Note however, that the evidence summarised above consider only variations in utilisation rates, but it does not account for differential costs for similar episodes of care that would also influence variations in spending. For instance, previous evidence on length of stay after hip replacement have found that individuals from the most deprived areas tend to stay longer in hospital and thus cost more to treat (Cookson & Laudicella, 2011).

With regards to inequities in cancer spending, considerable variations across Primary Care Trusts (PCTs) have been found after adjusting for local cost and need variation factors. Expenditure on cancer was found to vary around 2.2-fold between Knowsley PCT spending £118 per head, compared with £53 by Bedfordshire PCT (Appleby & Gregory, 2008). Variations in spending on disease-specific programme are not unimportant, as they have been found to have an impact on health outcomes. The effect of health care spending on health outcomes such as disease-specific mortality and years of life lost (YLL) have been recently estimated using the Programme Budgeting data (Martin *et al.*, 2008; Martin *et al.*, 2011). The authors found that after accounting for endogeneity, expenditure on cancer services significantly reduces mortality from cancer. Similar results were found for other disease programmes.

7.3. Measurement and explanation of inequity using longitudinal data

7.3.1. Measurement of inequity using longitudinal data

Most analyses of equity in health and health care have focused on measures of inequalities designed for use with cross sectional data as used in this thesis. However, Jones & López-Nicolás, 2004 emphasised the desirability of the longitudinal perspective in the measurement of income-related inequalities in health. They proposed a measure of health inequality inspired in the literature of income mobility

(Shorrocks, 1978). This approach considers inequality in health averaged across a sequence of periods of time across the distribution of income averaged across this sequence of periods of time. The advantage of this approach is that it accounts for potential systematic differences in health among individuals who are upwardly (income) mobile and downwardly mobile. They found that measuring longer term health inequality by simply taking a weighted average of the inequality estimated in each year tends to underestimate long-run inequality as measured in their proposed way. Bago d'Uva *et al*., 2009 applied a similar methodology to the context of horizontal inequity in health care. They also found that panel-based methods lead to significantly higher estimates of horizontal inequity.

Following Jones and López-Nicolás, 2004, we take the longitudinal approach for the measurement of inequity in health care spending. Long-run (LR) inequality in health care spending is measured as the concentration index, CI_T, for the average actual expenditure across periods, using as ranking variable the average need or deprivation measure across periods. Only when variations in the ranking variable across time are not associated with systematic differences on the spending distribution, this measure of inequality equals the weighted average of the short-run (ASR) concentration indices defined as,

$$CI^{ASR} = \sum_t w_t CI_t \text{ , where } w_t = \frac{\bar{q}_t}{T\,\bar{\bar{q}}_T} \qquad (7.1)$$

where T is the number of periods, $\bar{q}_t$ is the average spending in period t, and $\bar{\bar{q}}_T$ is the average spending across the T periods. Recall that the CI lies between –1 and +1, with positive values indicating a pro-rich (pro-healthy) concentration of health care resources across the socioeconomic (need) distribution.

Similarly to the cross sectional estimates, long-run horizontal inequity can be measured as the difference between the CI_T of actual utilisation and the CI of the average need predicted health care spending across periods[19],

$$HI_T = CI_T - CI(\hat{q}_i) \qquad (7.2)$$

[19] In the context of linear models, this approach lead to the same results than those derived using the standardisation approach for the computation of the indices of horizontal and vertical inequity.

Where need-predicted health care spending is created using a regression model of health care expenditure against a number of need and non-need variables, and neutralising the effect of the non-need variables by setting the variables equal to their mean values,

$$\hat{q}_{it} = \alpha + \sum_k \hat{\beta}_k N_{itk} + \sum_j \hat{\delta}_j \overline{Y}_{itj} + \varepsilon_{it} \tag{7.3}$$

where *i* indexes individuals (PCTs in our analysis) and *t* indexes time periods. We measure long-run vertical inequity as the difference between the CI of the average need predicted allocation and the CI of the average target allocation across periods of time.

$$VI_T = CI(\hat{q}_i) - CI(q_i^*) \tag{7.4}$$

The target allocation is given by Equation (7.5), where the need variables have the optimal effect on spending (details for estimation of the optimal effect of the need variables are provided below) and the effect of the non-need variables are again neutralised,

$$q_{it}^* = \alpha + \sum_k \beta_k^* N_{itk} + \sum_j \hat{\delta}_j \overline{Y}_{itj} + \varepsilon_{it} \tag{7.5}$$

Finally, long-run total inequity is measured as the difference between the CI of the average actual spending and the CI of the average target expenditure allocation over time,

$$TI_T = CI_T - CI(q_i^*) \tag{7.6}$$

We measure horizontal, vertical and total inequity using a measure of need and a measure of deprivation as ranking variables to compute need-related and socioeconomic-related inequity, respectively. Horizontal inequity is measured using the conventional and the conservative approach illustrated in the previous chapter, the difference between the two being that the later excludes the error term from the horizontal inequity estimate (Bago d'Uva *et al.*, 2009). The population size of each PCT is accounted for by using them as weights in the computation of the concentration indices.

7.3.2. Explanation of inequity using longitudinal data

We decompose the indices of inequality in health care spending by the contributor factors using the same methodology as explained in previous chapters of this thesis. In the case of using longitudinal data the decomposition of inequality in health care expenditure is defined as (Jones & López-Nicolás, 2004),

$$CI_T = \sum_k \left(\frac{\beta_k \overline{N}_k}{\overline{\overline{q}}_T}\right) CI_T^k + \sum_j \left(\frac{\delta_j \overline{Y}_j}{\overline{\overline{q}}_T}\right) CI_T^j + \frac{GC_\varepsilon}{\overline{\overline{q}}_T} \quad (7.7)$$

where $\overline{N}$ and $\overline{Y}$ are the mean values of the need and non-need variables; CI_T^k and CI_T^j are the CI of the average need and non-need variables with respect to the average of the ranking variable across time; and GC_ε is the generalized concentration index (CI times the mean) for the error term.

The individual contribution of each of the non-need variables to inequality in health care spending provides the decomposition of horizontal inequity. Similar to the methodology presented in an earlier chapter, we propose to decompose the vertical inequity estimate by looking at the differences for each of the need indicators included in the regression between the contribution of the need indicator based on its estimated and its target effect on spending,

$$VI_T = \sum_k (\hat{\beta}_k - \beta_k^*) \frac{\overline{\overline{N}}_k}{\overline{\overline{q}}_T} CI_T^k \quad (7.8)$$

7.4. Empirical models and estimation methods

We adopt a similar estimation strategy as that proposed by Cornwell & Ruppert, 1988 and followed by Contoyannis and Rice, 2001. Our model of health care spending across five years of data is regressed against a number of time variant and time invariant covariates among the need and non-need indicators. Our specification of the expenditure equation in the context of longitudinal data is thus,

$$q_{it} = \alpha + \sum_k \beta_k N_{itk} + \sum_h \gamma_h N'_{ih} + \sum_j \delta_j Y_{itj} + \sum_l \varphi Y'_{il} + \alpha_i + \varepsilon_{it} \tag{7.9}$$

where N_{it} and Y_{it} are need and non-need time varying regressors, respectively including cancer cases, mortality, and job seekers claimants. N'_i and Y'_i are time-invariant need and non-need variables, respectively including a cancer severity index and large geographical area indicators. α_i is an area specific and time invariant error component (known as the unobserved individual effect); and ε_{it} is a classical idiosyncratic disturbance. We assume that ε_{it} are uncorrelated with both the explanatory variables and the effects α_i.

Ordinary Least Square (OLS) and random effects (RE) models assume the covariates to be uncorrelated with the unobserved individual effect. However, the unobserved individual effect α_i might be correlated with (be endogenous to) some covariates in the model, and this can be controlled for in the specification of the econometric model using specific panel data techniques. The traditional solution in the presence of correlation of α_i with the covariates in the model is to use fixed effects (FE) (also known as 'within' estimators) which transform the data into deviation from the individual means. The major limitations of this method are that time invariant variables cannot be included in the analysis and that it is not fully efficient as it ignores variation across observations. Hausman and Taylor (HT), 1981 and Amemiya and MaCurdy (AM), 1986 proposed instrumental variable (IV) specifications using internal instruments that control for the correlation of the unobserved individual effect and the covariates suspected to be endogenous[20]. These estimators have the advantage of allowing time invariant variables to be included. In addition, they are generally more efficient than fixed effects estimators as they exploit the assumptions about which explanatory variables are exogenous.

[20] There is an additional variant of the IV estimators proposed by Breusch, Mizon and Schmidt, 1989 which is not considered in this analysis.

We experiment with simple OLS regressions that allow for clustering at the PCT level and RE specifications which assume exogeneity. Validity of the OLS model can be tested by running a RE model and performing the Breusch-Pagan test. Hausman test are carried out to test for the correct specification (exogeneity) of the random effects estimates, i.e. under the null of exogeneity the fixed effects estimates should be close to the random effects estimates for the time varying variables. Time invariant variables cannot be compared as the fixed effects specification does not allow its inclusion. Therefore, even in the case that the Hausman test does not reject exogeneity of the time variant covariates, the use of the IV estimators may be preferred as they allow for the inclusion and potential endogeneity of time invariant covariates (Contoyannis & Rice, 2001). For the IV estimators it is necessary to consider a priori partitioning of the variables into exogenous and endogenous components. Consider the change in notation where we now define X_{it} a vector of 1xG regressors that include both need and non-need indicators that are time-varying, and Z_i a vector of 1xH regressors that include both need and non-need indicators that are time-invariant. Following this notation we partition X and Z such as:

$$X = (X_1, X_2),\ Z = (Z_1,Z_2) \qquad (7.10)$$

and assume X_2 and Z_2 are correlated with the individual effects α_i, while X_1 and Z_1 are not. Note that X_1 has g_1 columns, X_2 has g_2 columns, and $g_1+g_2=G$; Z_1 has h_1 columns and Z_2 has h_2 columns, and $h_1+h_2=H$. The HT estimator uses the instrument set:

$$HT = (X_1 - \overline{X}_1, X_2 - \overline{X}_2, \overline{X}_1, Z_1) \qquad (7.11)$$

Where the time varying endogeneous variables are instrumented using the deviation from their means values. The mean values of the assumed time-varying exogeneous variables are used to (over) identify the parameters of the time invariant endogenous variables. Note that each variable in X_1 provides two instruments since the means, $\overline{X}_1$, and deviations from the means, $X_1 - \overline{X}_1$, are used separately. The order condition for the HT estimator to exist is $g_1 \geq h_2$.

The AM estimator uses the level of each time varying exogenous variable at each time period *t* defined by X_{1i}^* to instrument the time invariant endogenous variables. The set of instrument is thus defined as:

$$AM = (X_1 - \overline{X}_1, X_2 - \overline{X}_2, X^*_1, Z_1) \qquad (7.12)$$

Therefore, while HT uses each X_1 variable as two instruments, AM uses each of these variables as (T+1) instruments, i.e., $X_1 - \overline{X}_1$ and X^*_1. The AM order condition for existence is $Tg_1 \geq h_2$.

In both cases the models would be inconsistent if some of the variables assumed to be exogenous are correlated with α_i. We can test for this by running a Hausman test that compares the fixed effect estimates with both the HT and AM estimates. If consistent, the AM estimates provide potential efficiency gains over the HT estimators.

It is important to be aware of some of the assumptions which are required for the above estimators. Centrally, we assume throughout that the potentially endogenous variables are correlated with the individual specific and time invariant component of expenditure but not with the period and individuals specific error which determines expenditure. Therefore, we assume that a number of indicators might be endogenous in a model of cancer expenditure, but not simultaneous. Furthermore, the validity of our approach is dependent on the hypothesis that any serial correlation in the error term of the expenditure equation is due to the individual specific component. Thus even if expenditure does not affect contemporaneously our endogenous indicators, 'simultaneity' might be introduced if there is serial correlation in the period and individual specific error which determines expenditure.

We applied bootstrapping techniques using 500 replications to compute standard errors (SE) around the estimates of HI, VI, and TI. Following similar methods as in previous chapters, bootstrapping techniques are also used to estimate the SEs to assess the statistical significance of the contribution of the individual covariates to explain the observed inequities. Therefore, the bootstrapping process includes the model estimation for the need-predicted allocation and the model estimation for the target allocation of spending in order to derive SEs for the indices of inequity and around the contribution of the each covariate to our measures of inequity.

7.5. Data

Table 7.1 summarises the data used in the models and as target indicators in the analysis. In Table 7.1 we include the name, description, summary statistics, availability by year, sources of the data and original geography availability of the data.

7.5.1. Expenditure on cancer

Programme budgeting is the analysis of expenditure in health care programmes. Data have been collected annually for 23 main programmes of care based on the World Health Organisation international Classification of Diseases (ICD10) – including cancer programme, since 2003/04. The data is available by Primary Care Trusts (PCT). Thus we use PCTs as unit of analysis in our models of which there were 152 at the time of the analysis with an average population of 330,000. PBD includes most items of publicly funded expenditure, including inpatient, outpatient and community care, and pharmaceutical prescriptions. The programme-specific figures do not include GP expenditure, social care expenditure, and prevention expenditure which are reported separately. The PCT level expenditure figures are for expenditure on own population which is net expenditure, adjusted to add back expenditure funded from sources outside of the NHS and to deduct expenditure on other PCTs populations through lead commissioning arrangements. We use data for PCTs on "Expenditure on own population (£000s)" for the financial years (FY) 2004/05 until 2008/09. We regress total spending on cancer against a number of need and non-need indicators. The reason for looking at total expenditure rather than expenditure per head or per case is that if expenditure is not proportional to cases (some cases cost more than others), a model that uses expenditure per case as the dependent variable would be misspecified (Gravelle & Hole, 2008). Therefore, we focus on total expenditure and include total count of cases and total populations in the spending equation.

Data for the financial years 2004/05 and 2005/06 were presented for the old 303 PCTs structure (PCTs were reduced from 303 to 152 in October 2006). In order to pool the data, we use the PCT Mapping tool available from the NHS Information Centre[21] to present the data for every financial year based on the new 152 PCTs structure.

Raw figures of PCT expenditure do not adjust for unavoidable geographical variation in costs. This adjustment is necessary because, for instance, input prices in London and the South East of England are up to 30% higher than elsewhere (Martin *et al.*, 2008).

[21] http://www.ic.nhs.uk/statistics-and-data-collections/population-and-geography/pct-mapping-tool

Table 7.1. Description and (population-weighted) summary statistics

Name	Description	Mean	SD	Years	Source	Original Geography
Expenditure	Total expenditure on cancer programme (£000)	36,918	20,702	2004/05-2008/09	PBD	PCT
Cancer cases	Cancer cases diagnosed after 2003 (excluding non-melanoma skin cancer)	4,333	3,141	2004/05-2008/09	QOF	PCT
SMR cancer	Indirectly SMR from all cancers	102.3	10.940	2004-2008	ONS	PCT
EQ5D cancer	Cancer severity index	0.720	0.588	Time invariant	HSE	SHA
Population	Total population size	334,092	189,313	2004-2008	ONS	MSOA
Age09p	Population aged 0-9, percentage	11.618	1.178	2004-2008	ONS	MSOA
Age1019p	Population aged 10-19, percentage	12.705	1.050	2004-2008	ONS	MSOA
Age2039p	Population aged 20-39, percentage	27.475	5.718	2004-2008	ONS	MSOA
Age4059p	Population aged 40-59, percentage	26.807	2.259	2004-2008	ONS	MSOA
Age6074p	Population aged 60-74, percentage	13.685	2.559	2004-2008	ONS	MSOA
Age75plusp	Population aged over 75, percentage	7.710	1.618	2004-2008	ONS	MSOA
Malesp	Males, percentage	49.105	0.640	2004-2008	ONS	MSOA
Job seekers	Job seeker allowance claimants working age group, counts	5,564	2,677	2004/05-2008/09	ONS	LSOA
IMD Education	Index of deprivation: Education Skills and Training, score	21.592	8.878	2004 & 2007	ONS	LSOA
Whitep	White, percentage	90.362	10.719	2004-2007	ONS	LSOA
Asianp	Asian, percentage	5.475	6.913	2004-2007	ONS	LSOA
Blackp	Black, percentage	2.754	4.319	2004-2007	ONS	LSOA
Chinp	Chinese, percentage	0.729	0.547	2004-2007	ONS	LSOA
Otheretp	Other ethnic, percentage	0.682	0.686	2004-2007	ONS	LSOA
Number GPs	All Practitioners (head count) per 100,000 population	66.478	8.113	2006-2008	GMS	PCT
GP distant	Average Road Distance to GP Premises (Km)	1.524	0.698	2004 & 2007	ONS	LSOA
Inpatient capacity	Average capacity at acute providers	213,077	24,198	2004/05	CARAN	MSOA
Inpatient distant	Average distance to acute providers	12.790	6.761	2004/05	CARAN	MSOA
Northwest	Strategic Health Authority: North West	0.136	0.343	Time invariant	QOF	N/A
Northeast	Strategic Health Authority: North East	0.050	0.219	Time invariant	QOF	N/A
Yorkshire	Strategic Health Authority: Yorkshire	0.101	0.302	Time invariant	QOF	N/A
Eastmid	Strategic Health Authority: East Midland	0.085	0.279	Time invariant	QOF	N/A
Westmid	Strategic Health Authority: West Midland	0.106	0.308	Time invariant	QOF	N/A
Easteng	Strategic Health Authority: East of England	0.110	0.313	Time invariant	QOF	N/A

Name	Description	Mean	SD	Years	Source	Original Geography
London	Strategic Health Authority: London	0.149	0.356	Time invariant	QOF	N/A
Southeast	Strategic Health Authority: South East	0.083	0.277	Time invariant	QOF	N/A
Southcent	Strategic Health Authority: South Central	0.079	0.269	Time invariant	QOF	N/A
Southwest	Strategic Health Authority: South West	0.101	0.302	Time invariant	QOF	N/A
SMR CHD	Indirectly SMR from CHD	114.9	21.561	2004-2008	ONS	PCT
SMR COPD	Indirectly SMR from COPD	102.0	29.539	2004-2008	ONS	PCT
SMR stroke	Indirectly SMR from stroke	110.5	17.522	2004-2008	ONS	PCT
Variables used to select target groups						
SMRcanc75	Indirectly SMR from all cancers, individuals under 75	100.7	12.866	2008/09	ONS	PCT
Survbladder	5-year survival rate following diagnosis of bladder cancer	54.589	1.930	2008	ONS	SHA
Survbreast	5-year survival rate following diagnosis of breast cancer	81.478	0.850	2008	ONS	SHA
Survcervical	5-year survival rate following diagnosis of cervical cancer	63.656	1.752	2008	ONS	SHA
Survcolon	5-year survival rate following diagnosis of colon cancer	49.656	1.474	2008	ONS	SHA
Survlung	5-year survival rate following diagnosis of lung cancer	7.244	0.513	2008	ONS	SHA
Survesop	5-year survival rate following diagnosis of oesophagus cancer	10.389	1.244	2008	ONS	SHA
Survprost	5-year survival rate following diagnosis of prostate cancer	77.822	3.075	2008	ONS	SHA
Survstoma	5-year survival rate following diagnosis of stomach cancer	14.689	0.999	2008	ONS	SHA
Compliant62	Compliance with 62-day treatment standard	0.846	0.361	2008/09	CEP	PCT
Reftww	Referrals per 10,000 population through two-week wait	175.1	37.203	2008/09	CEP	PCT
Diagtww	Cancer patients diagnosed through two-week wait referrals, proportion	0.451	0.075	2008/09	CEP	PCT
Screcervical	Cervical cancer screening programme coverage, proportion	0.793	0.036	2008/09	ONS	PCT
Screbreast	Breast cancer screening programme coverage, proportion	0.758	0.070	2008/09	ONS	PCT
Emerlung	Lung cancer diagnoses after emergency admission, proportion	0.287	0.058	2005/06	HES	SHA
Emerpancreas	Pancreas cancer diagnoses after emergency admission, proportion	0.308	0.089	2005/06	HES	SHA
Compet2	World Class Commissioning Competency 2 Level 2 and above	0.948	0.222	2008/09	DoH	PCT
Compet5	World Class Commissioning Competency 5 Level 2 and above	0.729	0.445	2008/09	DoH	PCT
Compet6	World Class Commissioning Competency 6 Level 2 and above	0.442	0.497	2008/09	DoH	PCT

Note: SD = Standard deviation; SMR = standardised mortality ratio; PBD = Programme Budgeting Data; HSE = Health Survey for England; ONS = Office of National Statistics; QOF = Quality and Outcome Framework; GMS = General Medical Services Statistics; HES = Hospital Episode Statistics; DoH = Department of Health; CHD = coronary heart disease; COPD = Chronic obstructive pulmonary disease, LSOA = Lower Super Output Area; MSOA = Middle Layer Super Output Area; SHA = Strategic Health Authority; CEP = Cancer Equality Portal; PCT = Primary Care Trust; N/A = Not Applicable

The Hospital and Community Health Services Market Forces Factor (HCHS MFF) is used to achieve this cost adjustment. This data is available from the Department of Health Exposition Book[22].

7.5.2. Need indicators

We try and include a large set of clinically relevant need indicators that capture the number as well as the severity of cancer cases across areas. The variables considered to be need indicators are:

- Number of cancer cases: The data are taken from the Quality and Outcome Framework (QOF) maintained at the NHS Information Centre of Health and Social Care (www.ic.nhs.uk). The QOF was introduced in the UK in 2004 and requires general primary care practices to report their achievement on a number of quality indicators. Prevalence data for 11 disease domains from 2004/05 are collected and available until 2009/10 by PCT. The QOF information on the count of registered cancer cases is based on all cancers (excluding non-melanoma skin cancer) but include only patients diagnosed after 1st April 2003[23]. Similarly to expenditure data, data for the FY2004/05 and FY2005/06 were reported using the old 303 PCT structure, and therefore, data on counts of cases were converted to the new 152 PCT structure using the PCT Mapping Tool. We expect the number of cancer cases in each PCT to have a positive impact on cancer spending.
- Standardised mortality ratios from all cancers: Data on standardised mortality ratios (SMR) from all cancers from 2004 to 2008 were taken from the Office of National Statistics (ONS) (www.nchod.nhs.uk). We consider the SMR from cancer to be a proxy of the severity of cancer cases in each PCT, and thus we expect the variable to be positively correlated with expenditure. Alternatively, we used the observed number of deaths from cancer and found very similar results as shown in this chapter (results presented in Appendix 7.1). Note that larger expenditures on cancer could reduce mortality; however, given that our mortality data is slightly lagged with respect to the expenditure data (it is based

[22] http://webarchive.nationalarchives.gov.uk

[23] Note that by definition of QOF register data, individuals diagnosed with cancer before 2003 are not included in the indicator of the number of cancer cases. This implies that not every individual who suffer from cancer is included in the data. However, this is the case for every PCT and therefore it is unlikely to affect our results in the case that incidence rates of cancer were relatively stable across PCTs before and after the date cut-off used in the definition of the register.

on natural years rather than financial years) and that treatment would necessarily have a lagged effect on health outcomes, we do not expect reverse causality between spending and mortality in our analyses.

- Total population: Number of individuals in each PCT based in mid-year population estimates for Middle Layer Super Output Areas (MSOAs) by year available from the Office of National Statistics. We expect the size of the population to have a positive effect on total cancer spending over and above the count of cancer cases due to, for instance, running tests and procedures to individuals who eventually have a negative cancer diagnosis.
- Age profile: Percentage of the population in age bands: 0-9, 10-19, 20-39, 40-59, 60-74, 75 and over, based in mid-year population estimates for MSOAs by year extracted from the Office of National Statistics. We expect populations with larger percentages in the oldest age categories to have a positive impact on spending, due to, for instance, longer hospital stays.
- Gender: Percentage of males in the population based in mid-year population estimates for MSOAs by year available from the Office of National Statistics. Due to the various types of cancers included in the analyses we do not have an expectation with respect to the impact of this variable.
- Predicted mean EQ-5D of individuals suffering from cancer: We create a cancer severity index using information from the Health Survey for England (HSE) combining information from the years 2004-2006 and 2008 where EQ-5D data were available. The geographical unit available in these survey years in the HSE are the 10 Strategic Health Authorities (SHA). We compute a PCT-specific cancer severity measure by:
    a. Regressing EQ-5D scores among individuals reporting cancer using an OLS model against a number of individual and area level variables at the SHA level. The individual level variables included are: a cubic function of age and its interaction with gender, gender, and the presence and number of other longstanding illnesses. The SHA level variables included in the model are: percentage of individuals in different age group, percentage of males and percentage of individuals in various ethnic groups. The model also controls for year.
    b. Multiplying the estimated effect of the individual level variables by their SHA-specific mean values and adding this to the constant to create a SHA-specific constant term.

c. Adding this to the estimated coefficients of the area level variables multiplied by the PCT level version of these area level indicators. Therefore, individual level variables are used to create a constant SHA-specific value to which we add the effect of the area level variables estimated using information at the SHA level but then used to predict EQ-5D at the PCT level.

This variable takes larger values for better levels of health, so we expect the impact of the cancer-severity index to be negative on cancer spending.

7.5.3. Non-need indicators

Additional data on socioeconomic area characteristics is included in the analysis. The following variables are considered non-need indicators for cancer expenditure:

- Job seekers' allowance claimants: We include data on the number of benefit claimants in the working age group for job seeker allowance benefit. This data are available for every year of interest and reported in August, November, February and May each year. We compute the proxy of the mean number of claimants in each financial year by calculating the mean number of claimants reported in May, August and November in the initial year and February in the next year. Data were taken from the Neighbourhood Statistics at the Office of National Statistics (www.neighbourhood.statistics.gov.uk). The Neighbourhood statistics data are generally publish for small areas such as at the Lower Layer Super Output Areas level which are then mapped to the new 152 PCT structure.
- Education score: Extracted from the Neighbourhood Statistics, the Index of Multiple Deprivation (IMD) Education Skills and Training score for 2004 (used for 2004/05, 2005/06 and 2006/07) and 2007 (used for 2007/08 and 2008/09).
- Ethnicity: Percentage of individual in ethnic groups: White, Asian, Black, Chinese, and 'Other' extracted from the Office of National Statistics (data from 2007 is used for 2008/09). This measure provides an estimate of the percentage of residents of various Ethnic groups using as baseline the information from the 2001 Census.
- Severity in other disease domains: We proxied severity in other disease programmes by the SMR from coronary heart disease (CHD), chronic obstructive pulmonary disease (COPD) and stroke extracted for every year of interest from the Office of National Statistics. This is a similar approach to that

taken in Martin *et al.*, 2008 and Martin *et al.*, 2011, as those are competing disease programmes that attract considerable expenditure[24]. We expect severity in other disease domains to potentially affect how much is spent on cancer in each PCT. However, each PCT would have ideally receive enough budget to account for the severity in each disease domain (i.e. two individuals with the same need for cancer care should not receive different treatment due to differences in the severity level of other diseases in the population of the area where they live).

- Number of GPs per 100,000 population: The General Medical Services Statistics maintained at the NHS Information Centre of Health and Social Care (www.ic.nhs.uk) provides data on primary care workforce. Data is available using the new 152 PCT structure from 2006. Previous data are reported using the old PCT structure. The PCT Mapping Tool is not suitable for workforce data[25] and therefore we use data on general practice supply only for the years 2006-2008 (2006 values are used for 2004/05 and 2005/06).
- Average distant to GP premises: Taken from the IMD – Mobility scores for 2004 (used for 2004/05, 2005/06 and 2006/07) and 2007 (used for 2007/08 and 2008/09).
- Average capacity at acute providers: Average number of beds from each MSOA of the hospital actually used by its residents in 2004/05 using data from Hospital Episode Statistics and created for the CARAN report (Morris *et al.*, 2007).
- Average distance to acute providers: Average distance from each MSOA to the hospitals actually used by its residents in 2004/05 using data from Hospital Episode Statistics and created for the CARAN report (Morris *et al.*, 2007).
- The models also include year indicators.

The reason for not including other potential candidates of deprivation measures such as total scores of the IMD, incapacity benefit claimants, carer benefit claimants, disability benefit claimants, etc. is that these variables are partly a measure of ill health and partly a deprivation measure, and are thus difficult to categorise into a need or a non-need indicator.

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[24] Alternatively, we created a variable indicating the 'number of observed deaths not from cancer' (i.e. number of observed deaths from all causes minus number of observed deaths from cancer); however due to collinearity problems with the observed deaths from cancer and with the SMR from cancer indicator we could not include this variable.

[25]http://www.ic.nhs.uk/webfiles/Popgeog/PCT%20Spreadsheet%20Mapping%20Tool.doc

A number of variables included in the model are also difficult to categorise into need and non-need indicators of cancer spending. These are particularly the health care supply and the regional indicators defined by the 10 SHAs. If our measures of need summarised in section 7.4.1 were capable of fully capturing the need for cancer spending across PCTs, these indicators of supply and larger geographical area would be seen as measures of non-need factors. However, and especially in the context of area level analyses, these explanatory variables may be picking up unobserved need factors. Therefore, we run a sensitivity analysis where these variables are included among the need factors and among the non-need factors, respectively.

7.5.4. Target indicators

As emphasised in this thesis, the underlying assumption behind the horizontal inequity analysis is that the estimated effects of the need indicators on spending recovered from the regression model across the full sample are appropriate. We challenge this assumption and seek to identify subsamples of PCTs that best meet the need of their population by allocation resources appropriately according to needs. We use a series of indicators that fall into four different categories; i) cancer outcomes, ii) treatment services and prevention, iii) World Class Commissioning (WCC) scores in relevant competencies (following Morris *et al.*, 2010 we used information on the PCT scores in competencies related to meeting population needs and reducing health inequalities; see Appendix 7.2), and iv) PCTs that allocate the largest amount of resources to the neediest areas.

In terms of the specific target indicators, the following 14 criteria were used to select PCTs to be included in the target group:

1. PCTs with lowest SMR from all cancers for individuals under 75 year-old in 2008/09 extracted from the ONS.
2. PCTs with best 5-year survival rates for eight types of cancers for individuals diagnosed in 2001-2003 and followed up to 2008 available in the ONS.
3. Compliance with the 62-day treatment standard for cancer in 2008/09. This measure shows compliance with the 62-day treatment standard between urgent referral and first treatment. The data are available in the Cancer Equalities Portal (http://www.ncin.org.uk/equalities/data.shtml).
4. PCTs with largest number of referrals per 10,000 population through two-week waits in 2008/09. This measure shows the number of cases (per 10,000 population

per year) referred as an urgent GP referral for suspected cancer (two-week wait). This referral route has been related to better outcomes for cancer patients (National Cancer Intelligence Network, 2010). The data are extracted from the Cancer Equalities Portal[26].

5. PCTs with largest proportion of cancer patients diagnosed through two-week wait referrals in 2008/09 (Cancer Equalities Portal). This measure shows the percentage of PCTs' patients diagnosed with cancer who were urgently referred for suspected cancer by their GP through the two-week wait pathway. Other patients will have been diagnosed through screening, emergency admissions and routine referrals.
6. PCTs with largest proportion of cervical cancer screening programme coverage among females aged 25-64 in 2008/09 (Cancer Equality Portal). This measure shows the proportion of the PCT's population eligible to be screened who are actually screened in the previous 5 years.
7. PCTs with largest proportion of breast cancer screening programme coverage among females aged 53-70 in 2008/09. This measure shows the proportion of the PCT's population eligible to be screened who are actually screened by the NHS Breast Screening Programme over the last three years[27].
8. PCTs with lowest proportion of lung cancer diagnoses after emergency admission in 2005/06 (latest data available) extracted from the Hospital Episode Statistics. This measure shows the percentage of hospital admissions with a diagnosis of lung cancer that were admitted to hospital through an emergency admission. This referral route has been related with worst cancer outcomes (National Cancer Intelligence Network, 2010).
9. PCTs with lowest proportion of pancreatic cancer diagnoses after emergency admission in 2005/06 (latest data available) extracted from the Hospital Episode Statistics. This measure shows the percentage of hospital admissions with a diagnosis of pancreatic cancer that were admitted to hospital through an emergency admission. This referral route has been related with worst cancer outcomes (National Cancer Intelligence Network, 2010)[28].

[26] http://www.ncin.org.uk/equalities/

[27] Screening coverage information by PCT was available for cervical cancer and breast cancer only.

[28] Percentages of emergency hospital admissions with a diagnosis of cancer were available for each type of cancer separately by Strategic Health Authority; lung and pancreatic cancer were found to be the types of cancer with largest percentages of emergency admission diagnosis, and with a negative relationship between cancer outcomes and this type of referral route.

10. Meeting WCC Competency 2 “Work collaboratively with community partners to commission services that optimise health gains and reductions in health inequalities” at level 2 or above in 2008/09.
11. Meeting WCC Competency 5 “Manage knowledge and undertake robust and regular needs assessments that establish a full understanding of current and future local health needs and requirements” at level 2 or above in 2008/09.
12. Meeting WCC Competency 6 “Prioritise investment according to local needs, service requirements and the values of the NHS” at level 2 or above in 2008/09.
13. PCTs with the largest coefficient of the number of cancer cases explanatory variable in our preferred regression model. Similarly to the approach taken in the AREA report (Sutton *et al.*, 2002) we run the preferred cancer spending model separately in every SHA. This yields 10 sets of regression results. We then select the SHAs with the largest, more positive, coefficients on the variable considered to be the best indicator for need of cancer spending, i.e. the number of cancer cases. The rationale for selecting these PCTs is that in some SHAs we may obtain larger coefficients than in others, which may be due to these SHAs being better able to meet the needs of local populations; we call these SHAs ‘responsive’.
14. PCTs with largest need index in our models. A potential problem with the above approach to identify ‘responsive’ SHAs is that in some responsive SHAs the coefficient on one needs indicator, such as count of cancer cases, may be higher than in an unresponsive SHA, but on another needs indicator, such as the severity index, it may be lower. However, the aggregate effect is that the first SHA is more responsive to local needs than the second. To account for this issue we can compute the combined effect of the coefficients by computing an indicative needs index for an area with a predefined set of characteristics. We follow the same approach than that used in the recent review of the resources allocation formulae undertaken in the CARAN report (Morris *et al.*, 2007). We run the preferred spending model separately in every SHA. We compute an indicative needs index for the average area using each set of coefficients by:
    a. Multiplying the coefficient on every non-needs variable (including the regional indicators and supply variables) by its SHA population-weighted mean value and adding this to the constant term in the SHA regression model.
    b. Adding to this the coefficient on every needs indicator multiplied by the national mean value of each needs indicator.
    c. Dividing the resulting variable by its population-weighted mean value to give an indicative additional needs index that is centred on unity. We label

this the ‘responsiveness score’. This yields 10 responsiveness scores; one based on each set of SHA coefficients.

Using this method, more responsive SHAs are those which generate a higher responsiveness score for the average area. We rank SHAs coefficients according to the value of the responsiveness score and we select the most responsive SHAs.

The baseline estimates of vertical inequity are computed using a combination of all the above target indicators defined as the 70% of PCTs meeting the largest number of the 14 individuals targets specified above. We consider the indicator to be met if the PCTs fall into the best 70% performers for those indicators that are specified as a continuous variable, e.g. 70% of PCTs with largest proportion of breast cancer screening programme coverage.

The rational for selecting a cut-off of 70% rather than, for instance 50% as Sutton *et al*., 2002 and Morris *et al.*, 2007, is that the number of observations in our data are considerably lower, and selecting the 50% would imply running our models on just over 70 PCTs. The 70% cut-off also allows us to have a similar number of observations under every target, and so it is not likely that differences in the results are driven by the different number of observations selected under different targets. For instance, some targets rely on data only available at the SHA level of which there are 10 in England. The closest consistent number involved selecting the best six SHAs in every case which included around the 70% of PCTs. Four indicators are given by whether the PCT meets or not a specific target, i.e. compliance with 62-day treatment (84%), achievement of level 2 or above in WCC Competency 2 (95%), achievement of level 2 or above in WCC Competency 5 (73%) and achievement of level 2 or above in WCC Competency 6 (43%). There is unavoidable variation in the number of observations for these target indicators.

7.6. Empirical results

7.6.1. Model results

Table 7.2 presents the summary statistics of total expenditure on cancer and cancer expenditure per capita across years. Total spending and expenditure per capita are increasing over time. The ranges of the variables reflect wide variation across PCTs. The analysis of the variation on expenditure per capita indicates that the average expenditure per capita across PCTs varied from £60 to £163 in 2008/09. However, these estimates do not account for variation in the needs for cancer spending across PCTs[29].

Table 7.2. Summary statistics of cancer expenditure across PCTs and over time

	Mean	SD	Min	Max
Total expenditure on all populations (£0,000)				
2004/05	£32,212	£17,980	£6,213	£78,113
2005/06	£35,504	£19,415	£6,729	£81,669
2006/07	£35,981	£20,869	£8,601	£100,355
2007/08	£39,670	£22,594	£9,095	£116,843
2008/09	£41,079	£21,334	£7,509	£99,059
Expenditure per capita (£)				
2004/05	£74.777	£15.194	£40.805	£136.768
2005/06	£81.991	£17.533	£35.612	£141.231
2006/07	£82.610	£19.384	£43.496	£157.169
2007/08	£91.271	£20.131	£47.742	£151.317
2008/09	£96.257	£17.863	£60.171	£162.719

Note: SD = standard deviation; min = minimum; max = maximum

Table 7.3 presents the results for the expenditure regression models. We compare OLS, simple random effects, fixed effects and the random effects instrumental variable estimators suggested by Hausman & Taylor and Amemiya & MaCurdy.

The pooled OLS model with PCT level clustering is rejected on the basis of the Breusch-Pagan test. The Hausman test does not reject the RE model; however, this test only compares the coefficient of the time-varying variables, and, further, the differences in the parameter estimates of a series of variables in the RE and FE models appear to justify scepticism in relation to this result. As noted above the FE model is limited by the fact that only time varying variables can be included in the analysis. The panel data IV estimators are capable of overcoming the problem of endogeneity and offer efficiency gains over the fixed effects estimators. Further, these estimators have the advantage over the FE and RE estimators of allowing the effect of endogeneous time-invariant variables to be consistently estimated.

[29] Note that as mentioned above QOF data on the count of cancer cases include only patients diagnosed after 1st April 2003. The number of cancer cases registered in QOF has increased substantially over time. The rise primarily reflects the cumulative accrual of new cancer cases onto practice registers with each passing year due to the date cut-off in the definition of the register. Therefore, the analysis of the expenditure per case across time using cancer cases information as provided by QOF is not informative.

Table 7.3. Models of expenditure on cancer programme (£0,000) across PCTs

	OLS		RE		FE		HT		AM	
	Coef	z	Coef	z	Coef	z	Coef	z	Coef	z
Cancer cases	1.050	2.94	1.170	4.92	1.441	3.66	1.336	5.57	1.283	5.42
SMR cancer	21.16	0.74	49.12	1.62	65.73	1.95	66.07	2.13	68.88	2.26
EQ5D cancer	-1862.2	-1.24	-3234.8	-2.37			-4915.7	-2.82	-4480.8	-2.69
Population	0.063	15.24	0.064	18.23	0.083	1.07	0.068	14.85	0.067	15.02
Age09p	-159.6	-0.26	59.26	0.08	1063.1	0.66	282.0	0.28	279.0	0.28
Age1019p	Base category		Base category		Base category		Base category		Base category	
Age2039p	-492.1	-0.96	-506.5	-1.05	669.4	0.55	-515.9	-0.78	-527.1	-0.82
Age4059p	-604.3	-1.23	-110.7	-0.19	2221.9	1.31	206.9	0.25	64.2	0.08
Age6074p	-533.4	-0.63	-1026.1	-1.41	370.6	0.21	-1277.5	-1.38	-1243.6	-1.36
Age75plusp	1626.0	2.40	2526.5	3.44	4085.7	1.96	3246.9	3.56	3141.5	3.46
Malesp	1862.3	1.81	2794.8	2.78	4409.4	2.31	3761.1	3.02	3627.4	2.98
Job seekers	0.952	3.35	0.748	3.44	-0.109	-0.29	0.163	0.50	0.353	1.21
IMD Education	52.94	0.80	72.25	1.06	84.87	0.33	114.36	0.86	60.48	0.56
Whitep	Base category		Base category		Base category		Base category		Base category	
Asianp	-176.35	-2.93	-146.37	-1.93	-301.84	-0.24	-97.93	-0.82	-118.98	-1.02
Blackp	-43.39	-0.28	192.87	1.03	1239.66	1.47	543.30	2.06	450.92	1.76
Chinp	304.10	0.38	533.94	0.49	-176.17	-0.05	869.81	0.54	731.38	0.46
Otheretp	538.40	0.97	523.33	0.62	-3154.9	-0.83	158.31	0.13	200.88	0.16
Number GPs	23.09	0.69	-37.56	-1.02	-171.02	-3.12	-97.29	-2.26	-98.12	-2.29
GP distant	130.43	0.40	-72.55	-0.17	-284.43	-0.56	-240.70	-0.55	-231.36	-0.53
Inpatient capacity	0.009	0.64	0.004	0.19			-0.006	-0.19	-0.01	-0.15
Inpatient distant	-0.877	-0.01	29.55	0.42			40.96	0.37	35.54	0.32
Northwest	Base category		Base category				Base category		Base category	
Northeast	-1339.1	-1.51	-1076.1	-0.77			-441.7	-0.19	-347.5	-0.16
Yorkshire	-366.2	-0.31	-321.9	-0.24			-101.4	-0.04	146.6	0.07
Eastmid	-390.4	-0.18	-983.8	-0.59			-1900.4	-0.72	-1552.7	-0.60
Westmid	-3443.4	-3.20	-3643.2	-2.84			-3843.8	-1.92	-3713.3	-1.87
Easteng	-2085.2	-1.57	-2935.8	-1.79			-4371.1	-1.74	-4059.0	-1.62
London	450.4	0.28	-1254.0	-0.60			-3614.8	-1.10	-3284.1	-1.02
Southeast	-4050.2	-1.81	-5120.8	-2.71			-6461.5	-2.17	-6244.7	-2.11
Southcent	-6153.5	-3.48	-6944.9	-3.90			-8502.1	-3.06	-8146.1	-2.96
Southwest	-793.4	-0.57	-1042.7	-0.66			-1938.2	-0.78	-1668.9	-0.68
SMR CHD	29.13	1.82	18.84	1.04	10.20	0.47	12.87	0.68	14.57	0.77
SMR COPD	-5.42	-0.51	-3.29	-0.28	-2.02	-0.15	-1.35	-0.11	-0.62	-0.05
SMR stroke	14.14	0.84	20.71	1.29	19.92	1.11	20.63	1.28	21.41	1.33
y2005	1622.2	3.23	1487.3	2.75	1254.8	1.66	1472.4	2.65	1498.4	2.75
y2006	1046.5	1.38	698.3	0.91	100.5	0.08	546.2	0.64	637.4	0.78
y2007	3944.5	4.24	3525.6	3.86	2151.1	1.22	2928.4	2.85	3172.0	3.19
y2008	3421.1	2.96	3514.7	3.12	3267.9	1.53	3830.5	3.01	3856.5	3.11
N	760		760		760		760		760	
B-P test	143.520									
Hausman			23.820				8.050		2.680	
p-value	0.000		0.251				0.995		1.000	

Note: For variable definition see Table 7.1. OLS = Ordinary Least Square; RE = Random Effect; FE = Fixed Effect; HT = Hausman & Taylor; AM = Amemiya & MaCurdy; Coef = Coefficient; B-P = Breusch-Pagan

For the IV estimators it is necessary to consider a priori partitioning of the variables into exogenous and endogenous components. In our regression model it is likely that we are not capable of controlling fully for variation in needs for cancer expenditure. Therefore, a number of variables included in our model are likely to be correlated with unobserved measures of needs that are also correlated with expenditure on cancer. The following variables are thus considered to be correlated with the unobserved individual effect: number of job seekers' allowance claimants; index of multiple deprivation – education domain; standardised mortality ratio from all cancers; and mean predicted EQ-5D of individuals suffering from cancer.

The effect of the number of cancer cases in the QOF register is significant and positive in every model, indicating that the number of cancer cases significantly explain variation in expenditure, as expected. Our measures of severity defined by SMR from all cancers and the cancer-specific severity index become strongly significant and their effects are considerably larger after accounting for endogeneity. The size of the population is significant and positively related to total cancer spending in every model with the exception of the FE estimators which ignore variation across PCTs. Only the oldest age category has a significant and positive effect in every model; the percentage of males leads to higher cancer expenditure levels.

In the models that assume all the covariates to be uncorrelated with unobserved individual effects (OLS and RE models), the effect of the number of individuals claiming job seekers' allowance benefits is positive and significant. The variable becomes non-significant after allowing and controlling for endogeneity. This might suggest that the variable was picking up unobserved factors that correlated with expenditure, such as unobserved needs. The education score is non-significant even after accounting for its potential correlation with the area-specific and time invariant error term. The effect of ethnicity suggests that higher percentage of residents from Asian ethnic groups leads to lower cancer spending when all covariates are assumed to be exogenous, but the effect becomes non-significant when all or part of the explanatory variables are allowed to be endogeneous. In that case, the effect of percentage of Black ethnic residents becomes weakly and positive significantly correlated with cancer expenditure. In terms of the supply indicators, only the number of GPs shows a significant effect in the models that allow for endogeneity suggesting that the larger the number of GPs in the area the lower the spending on cancer treatment. There is some area variation as shown by the significance of some SHA indicators, and the effect of the severity in other disease domains proxied by SMR from CHD, stroke and COPD is found to be non-significant in every model. The year effects suggest that expenditure is increasing over time.

The Hausman test for the instrument sets used in the HT and AM estimators appear to be valid, enabling the use of the these models. The Hausman test that compares HT and AM does not reject the extra exogeneity assumption imposed by the AM estimator, which is thus preferred as it is generally more efficient. We focus hereafter on the results from the AM regression model in order to measure inequity in cancer spending across PCTs.

7.6.2. Equity estimates

Table 7.4 summarises the equity estimates in cancer spending. The indices of SES-related inequity are measured using the number of job seekers' benefit claimants as the ranking measure, while the need-related indices are computed using the number of cancer cases as the ranking variable. We found similar results when using the observed number of cancer deaths as the ranking variable (the correlation between the rank variable derived using the count of cases and the rank variable derived using observed deaths is 0.970). Additionally, we reach same conclusion when applying cases per capita and job seekers' claimants per capita indicators rather than total counts for the computation of the ranking variables (results presented in Appendix 7.3). The variables were transformed (100,000 minus actual count) to provide the standard interpretation of the equity estimates, where a negative CI indicates that the variable of interest is concentrated among more deprived/ill health groups. All the inequity indices and regression coefficients were found to be exactly the same (but with the opposite sign) before and after making this transformation.

The CI_T for actual spending shows that total cancer expenditure is concentrated on areas with larger number of cancer cases as well as on areas with larger number of job seekers' benefit claimants. Therefore there are pro-poor and pro-sick allocations of actual cancer expenditure. The indices of HI suggest that after controlling for the average effect of the need indicators, there is no evidence of statistically significant HI with respect to deprivation and needs. The HI index is negative (pro-poor) with respect to deprivation and positive (pro-healthy) with respect to needs. The conservative estimates lead to smaller indices of SES-related HI, while the need-related HI is found to be larger in absolute terms when we exclude the contribution of the error term; both indices remain statistically non-significant.

Table 7.4. Estimates of inequity in expenditure on cancer across PCTs

	SES-related		Need-related	
	CI	**CI/SE**	**CI**	**CI/SE**
Actual (CI_T)	-0.2252	-18.26	-0.3433	-31.03
Horizontal inequity				
Conventional	-0.0345	-1.40	0.0171	0.55
Conservative	-0.0187	-1.01	0.0199	0.90
Vertical inequity	0.0144	0.34	0.0802	1.55
Total inequity				
Conventional	-0.0202	-0.36	0.0973	1.38
Conservative	-0.0043	-0.08	0.1002	1.46

Note: SES = Socioeconomic Status; CI = Concentration Index; SE = Standard Error.

Standard errors are derived using bootstrapping techniques.

Baseline indices of VI presented in Table 7.4 employed the combined target group defined by the 70% of PCTs meeting the largest number of the 14 individual targets to measured vertical inequity. Appendix 7.4 shows the results when each of the 14 target indicators is used separately to select the PCTs that form the target group. There is some variation in the results for specific target indicators but the majority yield to the same trend as the baseline model results. The baseline results show that the VI indices with respect to need and with respect to deprivation are positive, indicating pro-rich and pro-healthy vertical inequity, respectively. The indices are considerably larger with respect to the need dimension than with respect to the SES dimension, but none of them reach statistical significance.

Overall, the index of total inequity with respect to deprivation is pro-poor, while the analysis with respect to the need dimension shows a pro-healthy total distribution of cancer expenditure across PCTs; however, none of the indices are significant, suggesting an equitable distribution of resources across the socioeconomic and across the need distribution in cancer spending.

In addition to the LR indices, we also compute the ASR inequity indices as the weighted average of the short-run inequity indices as explained in Equation (7.1). The ASR indices of inequity were based on the same model of health care spending run across the full sequence of periods of time. Therefore we assume that the coefficients of the covariates are constant over time (similar to Bago d'Uva *et al.*, 2009). An alternative specification would be to allow the year specific indices of inequity to be derived from year-specific expenditure models; however the small number of observation in each period precludes this approach. The results were found to be consistent in both cases suggesting that there is little PCT re-ranking across years with respect to their level of cancer cases and job seeker's claimants (results presented in Appendix 7.5). Furthermore, the results were also consistent to the assumption that the supply and regional indicators are capturing unobserved need factors and therefore included among the need indicators (see Appendix 7.6).

7.6.3. Results from the decomposition analyses

The decomposition approach helps us to understand the mechanisms behind the equity results found in these analyses and are presented in Table 7.5.

Not surprisingly, most of the variation in total cancer spending across both the need and the deprivation distribution is due to differences in the population size of the PCTs. The second largest contributor is in both cases the number of individuals registered with a cancer diagnosis in QOF. The contributions of these two variables are strongly significant. The severity indicators make a modest contribution to the observed inequalities in expenditure, although the contribution of SMR from cancer is found to be significant in explaining variation across the need distribution. The role of the percentage of individuals in different age groups is driven by the contribution of the percentage of individuals aged 75 and older. This variable has a positive effect on spending and tend to be concentrated on richer areas but also in areas with larger number of cancer cases, contributing thus to a pro-rich but also to a pro-sick allocation of cancer expenditure. The opposite holds true for the case of the percentage of males in the population.

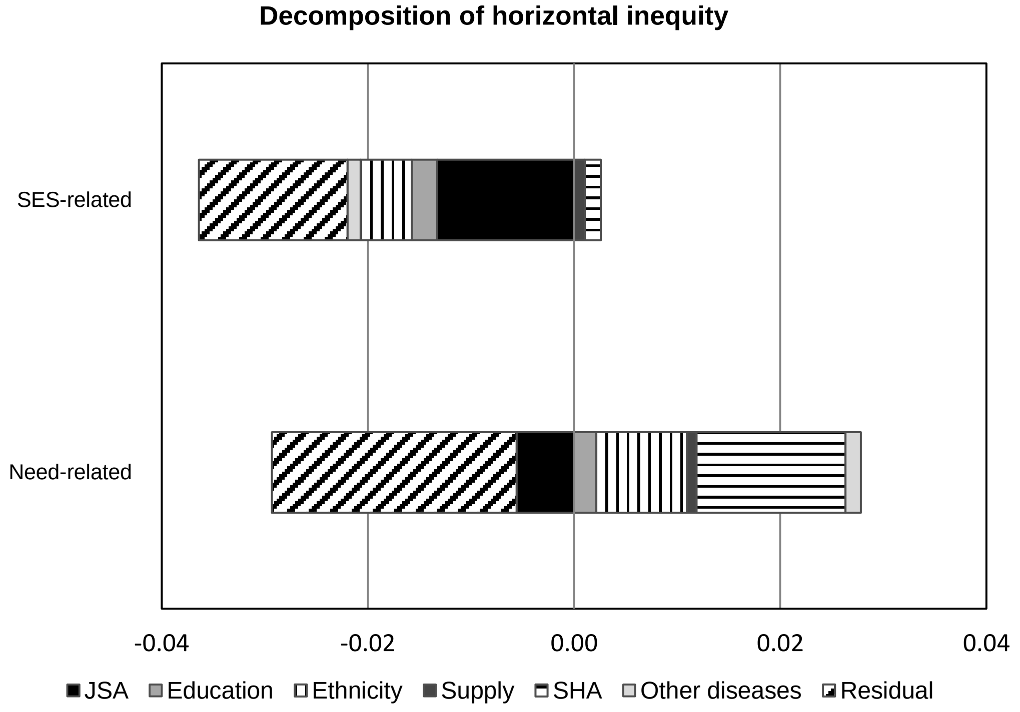
The contributions of the non-need variables explain the finding with respect to horizontal inequity and are graphically presented in Figure 7.1. None of the contribution of the individual non-need factors was found to be statistically significant (see Table 7.5). In the case of the SES-related HI we found that, at equal level of needs, cancer expenditure was concentrated on poorer areas, and a big fraction of this was due to the contribution of the error term. The next largest contributor is the number of job seekers' claimants. Education scores, ethnicity and the severity in other disease domains make a small contribution towards the pro-poor HI finding, while the contribution of supply and regional indicators leads to a more pro-rich allocation.

Table 7.5. Decomposition of inequity in expenditure on cancer across PCTs

		SES-related				Need-Related			
	Elasticity	CI	Cont	Percent		CI	Cont	Percent	
Cancer cases (-)	-3.327	0.008	-0.027**	12.1%	12.1%	0.014	-0.046**	13.5%	13.5%
SMR cancer	0.191	-0.011	-0.002	0.9%		0.020	0.004**	-1.1%	
EQ5D cancer	-0.087	0.016	-0.001	0.6%	1.5%	-0.024	0.002	-0.6%	-1.7%
Population	0.797	-0.211	-0.168**	74.8%	74.8%	-0.342	-0.273**	79.4%	79.4%
Age09p	0.088	-0.004	0.000	0.2%		0.024	0.002	-0.6%	
Age2039p	-0.393	-0.020	0.008	-3.5%		0.059	-0.023	6.8%	
Age4059p	0.047	0.012	0.001	-0.2%		-0.023	-0.001	0.3%	
Age6074p	-0.461	0.014	-0.006	2.9%		-0.062	0.029	-8.3%	
Age75plusp	0.657	0.018	0.012	-5.1%	-5.7%	-0.069	-0.045**	13.2%	11.4%
Malesp	4.829	-0.001	-0.005	2.4%	2.4%	0.002	0.010*	-3.0%	-3.0%
Job seekers (-)	-0.905	0.015	-0.013	5.9%	5.9%	0.006	-0.006	1.6%	1.6%
IMD Education	0.035	-0.069	-0.002	1.1%	1.1%	0.061	0.002	-0.6%	-0.6%
Asianp	-0.018	-0.110	0.002	-0.9%		0.261	-0.005	1.3%	
Blackp	0.034	-0.181	-0.006	2.7%		0.319	0.011	-3.1%	
Chinp	0.014	-0.059	-0.001	0.4%		0.133	0.002	-0.6%	
Otheretp	0.004	0.000	0.000	0.0%	2.2%	0.196	0.001	-0.2%	-2.6%
SMR CHD	0.045	-0.012	-0.001	0.2%		0.032	0.001	-0.4%	
SMR COPD	-0.002	-0.025	0.000	0.0%		0.069	0.000	0.0%	
SMR stroke	0.064	-0.012	-0.001	0.3%	0.2%	0.002	0.000	0.0%	-0.4%
Number GPs	-0.177	-0.006	0.001	-0.5%		-0.010	0.002	-0.5%	
GP distant	-0.010	0.018	0.000	0.1%		-0.151	0.001	-0.4%	
Inpatient capacity	-0.028	0.000	0.000	0.0%		-0.002	0.000	0.0%	
Inpatient distant	0.012	0.012	0.000	-0.1%	-0.5%	-0.189	-0.002	0.7%	-0.3%
Northeast	0.000	0.102	0.000	0.0%		0.279	0.000	0.0%	
Yorkshire	0.000	-0.332	0.000	0.1%		-0.130	0.000	0.0%	
Eastmid	-0.004	-0.663	0.002	-1.1%		-0.444	0.002	-0.5%	
Westmid	-0.011	-0.212	0.002	-1.0%		0.043	0.000	0.1%	
Easteng	-0.012	0.098	-0.001	0.5%		-0.239	0.003	-0.8%	
London	-0.013	0.102	-0.001	0.6%		0.442	-0.006	1.7%	
Southeast	-0.014	-0.239	0.003	-1.5%		-0.706	0.010	-2.9%	
Southcent	-0.017	0.126	-0.002	1.0%		-0.284	0.005	-1.4%	
Southwest	-0.005	0.340	-0.002	0.7%	-0.7%	-0.337	0.002	-0.4%	-4.2%
Total					93.3%				93.1%

Note: For variable definition see Table 7.1. SES= Socioeconomic status; CI = Concentration index; Cont = Contribution; Percent = Percentage contribution. Contributions with two and one star are significant at 5% and 10% level, respectively. Standard errors around the contributions are computed using bootstrapping techniques. Cancer cases and job seeker's allowance claimants indicators are transformed by subtracting the actual number from 100,000.

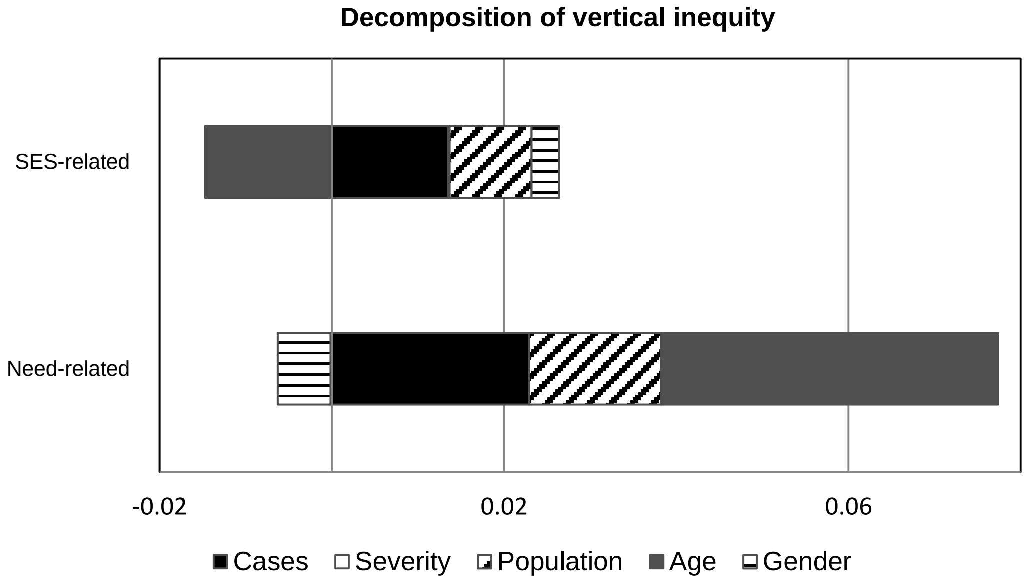
Figure 7.1. Decomposition of SES-related and need-related horizontal inequity



Moving to the need-related HI, we found a small and pro-healthy HI index. Interestingly, this result is not driven by the contribution of the number of job seekers' benefit claimants, as this variable contributes towards a pro-sick HI index. However, all the other non-need indicators including education scores, ethnicity, supply and regional indicators and severity in other disease domains contributes towards the pro-healthy HI finding. The largest contributor factors are the regional and ethnicity indicators as seen in Figure 7.1 for the estimated pro-healthy HI.

The individual contribution of each of the need variables to vertical inequity is represented graphically in Figure 7.2. The divergence from the estimated and the target effect of the age variables on spending makes the largest contribution to the estimated VI with respect to both need and deprivation rankings, followed by the contribution of the count of cancer cases variable. The role played by the differences in the estimated coefficients of the size of the population and the percentage of males is relative small in explaining the estimated VI.

Figure 7.2. Decomposition of SES-related and need-related vertical inequity



7.7. Discussion

In this chapter, we found that in the case of SES-related inequity estimates, the inclusion of vertical inequity considerations in addition to horizontal inequity did not affect substantially the magnitude of the estimated socioeconomic-related inequity in the allocation of cancer spending. However, when the need indicator was used as the dimension for the measurement of inequity, vertical inequity was found to be the main driver of observed total inequity in the allocation of cancer spending across the need distribution. Moreover, the inclusion of the need dimension in addition of the socioeconomic dimension in health care equity investigations provided valuable information; albeit its non-significant estimators, the total inequity indices were found to be negative, i.e. pro-poor, with respect the socioeconomic deprivation; while the indices were positive, i.e. pro-healthy, with respect to the need dimension.

The correlation of the need and deprivation variables is expected, and found to be positive. Therefore one would probably expect the results that measure inequity with respect to the need distribution and with respect to the deprivation distribution to show a similar trend. This is the pattern found for the distribution of actual spending on cancer. However in the case of horizontal inequity, the results suggest that the effect of the non-need variables favour a disproportionally larger allocation towards more deprived areas but also towards areas with lower number of cancer cases. The decomposition analysis sheds some light onto this result highlighting that the other non-need indicators – rather than job seekers' claimants – are responsible for the pro-healthy HI estimate across the need distribution. The role of the number of job seekers' allowance claimants worked on the same direction than in the case of the SES-related horizontal inequity contributing to a more pro-sick distribution, as expected. The differences in the magnitude of the consequences of vertical inequity across the need distribution and across the socioeconomic distribution also explained the divergence of the final results. The size of SES-related pro-rich vertical inequity is considerably smaller and not capable of compensating for the pro-poor level of HI inequity found. The large extent of pro-healthy vertical inequity drives the need-related total inequity result.

A limitation of this analysis is the small sample size. After incorporating the model uncertainty derived from the need-predicted and the target model estimation in the computation of the standard errors around the inequity estimates none of the inequity indices were found to be statistically significant. Ignoring the uncertainty due to the model estimation in the computation of the standard errors around the equity estimates lead to strongly significant estimates (results presented in Appendix 7.7). Therefore, the conclusions about the presence of an equitable distribution of cancer expenditure across PCTs need to be read with caution.

The generalisability of these results to other disease domains is not straightforward. Despite improvements in survival and mortality in recent decades, cancer outcomes in England remain poor when compared with countries with similar wealth (Department of Health, 2011). Special attention have therefore been drawn to cancer services, leading to the introduction of policies aimed at closing the gap in survival rates between England and European averages, and to reduce unacceptable variations in access to cancer services.   A number of guidelines setting national standards for effective cancer services and systems to monitor implementation were introduced in 2000 (Department of Health, 2000). Diagnosis of cancer at a late stage and a more advanced disease by the time the treatment begins are generally agreed to explain part of the low survival rates in England. Therefore, in addition to improving screening coverage and cancer symptom awareness, policies have aimed at reducing waiting times for cancer treatment by introducing explicit and cancer-specific waiting time targets. These include the maximum of two-weeks waiting from referral to an outpatient appointment for all suspected cancers; and a 62-days standard between urgent referral and first treatment. Therefore, given the emphasis on national standards and close monitoring for cancer care delivery, one might expect to observe less inequity in cancer service compared with other services. However, although there is evidenced that these waiting times targets are consistently achieved at a national level, some Trusts and local health economies have been found to struggle to achieve the standards (Department of Health, 2011). Further initiatives are currently being developed such as the introduction in 2008 of the National Cancer Equality Initiative[30] to help tackling inequalities in cancer outcomes and promote greater equality in all aspects of cancer service delivery.

The major advantages and limitations of analysis that uses national administrative data to identified health care inequalities rather than individual level information are summarised by Cookson *et al.*, 2010. They highlight that the two main advantages are that national administrative information includes almost everyone and everywhere in the country and that are routinely available every year. The main limitations are related with the considerable noise in the data due to ecological fallacies, unobserved geographical factors, and spatial autocorrelations. Appropriate control for variations in needs is possibly the most difficult challenge in investigations using geographical areas as the unit of analysis. Therefore, the aim of our analysis has been to maximise the extent to which variation in needs are captured, and therefore to reduce the impact of unobserved variables that might be driving differences in spending allocations. In our analysis we have tried to do this by including area level variables that capture both the number as well as the severity of cancer cases across regions in addition to using econometric techniques that facilitate the control for unobserved factors that might be correlated with the covariates in our models. Therefore, we expect the socioeconomic indicators labelled as non-need factors in our analyses to not pick up unobserved needs. However, none of these variables and techniques can offer a perfect substitute for unmeasured individual characteristics. In particular, cancer care has been argued to present many difficulties when assessing inequities. Dixon *et al.*, 2007 highlighted that these '*difficulties include the range of cancers and their aetiology, the impact of screening and the interpretation of case-mix adjustment'*. Furthermore, the econometrics techniques used in our analysis are aimed at controlling for endogeneity with respect to the unobserved individual effects, but they maintain the assumption that the covariates are uncorrelated with the idiosyncratic error disturbance.

The negative socioeconomic-related total inequity estimates suggest that cancer spending is concentrated on poorer regions. This might partly be a result of the reliance

[30] www.dh.gov.uk/en/Healthcare/Cancer/NationalCancerEqualityInitiative/index.htm

on socioeconomic indicators as measures of needs in the capitation formulae used to inform PCT revenue allocation in England. In the absence of good epidemiological data, the resource allocation formulae have largely relied on socioeconomic indicators as indicators of needs. However, given the positive sign and large magnitude of the need-related inequity indices, we have some evidence that health care spending on cancer is not appropriately concentrated on areas with larger cancer needs, and this is mainly driven by vertical inequities with respect to the need distribution. The vertical equity principle is not currently explicitly addressed in the resource allocation formulae. The principle underpinning the formula has traditionally focussed on ensuring ‘equal access for equal needs’. However, as already noted, in 1999 the Advisory Committee on Resources Allocation (ACRA) was asked by ministers to meet a second objective for resource allocation - to contribute to the reduction of avoidable health inequalities. This has led to inclusion of a ‘health inequality adjustment’ to account for this new criterion. This adjustment introduced in 2001/02 (but dropped from 2003/04 until 2008/09) is based on information on ‘difference from best’ disability free life expectancy across PCTs. For 2009/10 and 2010/11 PCT allocations, a 15% of the allocation was based on this formula. However, the recommendations on the form of this adjustment (and its weighting in the formula) were regarded as temporary, and a review to appraise different approaches was commissioned. Morris *et al.*, 2010 have recently conducted an appraisal of different approaches to the inclusion of the health inequality element of the capitation formula. One of their recommendations is the inclusion of an adjustment *‘to achieve funding capacity for appropriately unequal use for people with unequal needs’*, i.e. the explicit introduction of the vertical equity criterion on the resource allocation formula. The authors illustrate this approach using information from the World Class Commissioning (WCC) framework to identify PCTs that are better at aligning variations in resource use with variations in needs. However, they recommended that further work is undertaken to assess the suitability of the WCC framework for this purposed.

Therefore, more work needs to be done in order to firmly put back on the agenda considerations of vertical inequity aspects in the distribution of health care resources. The main issues in terms of data limitations and the lack of an explicit commitment with the vertical equity principle appear to be increasingly dealt with. The availability of newly collected epidemiological data within the Quality and Outcome Framework could provide the possibility of incorporating better indicators of needs; in addition, performance indicators are also increasingly collected and could thus be exploited for the estimation of the vertically equitable variation of health care resources with variation in needs. Finally, the recent emphasis and proposed recommendations for the introduction of a vertical equity criterion on the way health care resources are geographically allocated yield to the commitment of achieving vertical equity as a means to reduce avoidable inequalities in health.

CHAPTER 8

Conclusions of the analysis and some research and policy implications

8.1. Introduction

In this thesis we have examined in much detail the issue of vertical equity in the delivery of health care. The aim of the thesis was to provide a rigorous and quantitative analysis of vertical equity in the delivery of health care in England. We noted at the outset that although vertical equity considerations seem to be gaining momentum in the context of addressing inequalities and inequities in health and health care, vertical inequity analysis are rarely undertaken. Therefore, the aim of this thesis was to assess and refine the existing techniques to investigate vertical inequity, and to offer evidence about vertical equity in the English health care system.

To meet the general aims, the preceding six chapters of the thesis have provided a comprehensive examination of the inequality and inequity in health and health care in England. In Chapter 2, the extent of inequalities in health was investigated, accounting for variations over time and across regions in England. The third chapter provided an illustration of the methods commonly used in the literature to analyse inequity in the delivery of health care; the considered shortcomings were emphasised. In the subsequent four chapters we focused on the issue of vertical inequity by reviewing the empirical literature; by extending the most comprehensive methodology proposed to date; and by applying our suggested methods to the context of measuring inequity in individual level health care utilisation and in the context of area level spending of health care resources.

In this final chapter we summarise the earlier findings and then discuss some research and policy implications of the analysis. We then discuss some study limitations and offer some suggestions for future research.

8.2. Main findings

We began our analysis by examining inequalities in health in England. We analysed a large dataset providing very comprehensive information of individuals living in England from 1998 to 2006; and explored area variation across the nine Government Office Regions (GORs) in England. Rather than focusing on a simple dichotomous measure such as general self-assessed health or limiting illness status, as it is common practice in the inequality literature, we developed a comprehensive health index based on EQ-5D scores. This approach allowed us to consider the analysis of total inequalities in health in addition to the analysis of socioeconomic-related inequalities in health.

We found significant inequalities in health in England both with respect to total health inequalities and with respect to income-related inequalities in health over the period under analysis. The extent of health inequality (both in terms of income-related and total inequality) was found to vary between regions. We found a North-South gradient, previously reported in the literature both in terms of deprivation and health status, to also characterise the extent of inequalities in health in England. Furthermore, areas with relatively high level of inequality at the initial period were also experiencing the largest increases in inequality over time; while in the areas with relatively low levels, the estimates were found to decrease further during the period. These trends are thus exacerbating inequalities across areas in England.

The comparison between total health inequalities and the income-related inequalities in health suggested that socioeconomic inequalities in health are estimated to be around 30% of overall health inequalities. This result indicates that the social gradient in health inequalities is just a fraction of the overall dispersion in health in the population. Moreover, although some authors have highlighted the direct relationship between the concentration index of income-related inequalities in health and the Gini coefficient of overall health inequalities, we found that the choice between the Gini index and the CI as the measure of inequality in health is not unimportant. Conclusions about time trends and the ranking of areas in terms of the extent of inequalities in health were found to be sensitive to whether the definition of inequality includes full variations in health status or only those that are socioeconomically patterned. Whether the focus ought to be on reducing total inequalities in health or inequalities in health that are linked to socioeconomic factors is a matter of debate. We will consider this issue in the discussion of the implications for policy design of our analysis.

In Chapter 3 we presented the methods commonly used in the literature for the measurement of inequity in the delivery of health care, and applied them to the investigation of horizontal inequity in primary care services utilisation in England. The aim of this chapter was to highlight one of the main limitations of the vast majority of empirical analysis of inequity in health care to date, i.e. their solely focus on horizontal inequity. By presenting the methodology widely used in horizontal inequity analyses, we explicitly exposed the assumptions behind this approach. The use of the average effect of the need variables recovered from the regression analysis as the vertical equity norm was criticised. A close look at the estimated effect of the need indicators included in our analyses also helped us to emphasise that careful considerations about the appropriate effect of the need variables are required in order to make vertical equity judgments. For instance, we found that some morbidity indicators were not positively related with nurse visits. However, these patients were found to be significantly more likely to see a GP. The opposite held true for other health measures, such as an indicator of chronic disease. Therefore, these results may suggest a substitution between the patients being treated by each type of health professional and does not necessarily imply inappropriate use for different needs.

The analysis conducted in Chapter 3 also provides a contribution in terms of analysing horizontal inequity in primary care services. Unlike previous studies, which focus on GP service use only, we considered GP and practice nurse use, and allowed these types of use to be correlated. The role of practice nurses in primary care services in England have dramatically increased in recent times. Our results indicated that it is difficult to draw conclusions about the extent of primary care inequity based only on analyses of GP visits because practice nurses and GPs see different types of patient; inequities in the use of one type of care may be offset by the other type of care. We found that while there is horizontal inequity in favour of poorer individuals in the use of GP services, the estimate of horizontal inequity in practice nurse consultations use was found to be pro-rich but non-significant. Therefore, we consider the assessment of alternative health contacts to be necessary in order to draw any conclusion about inequity in the provision of health care services.

An additional methodological contribution was provided in Chapter 3 which related to the statistical inference of the horizontal inequity estimates. We found that the standard practice of deriving the standard errors around of the point estimate of the concentration index of the need-standardised allocation underestimates the uncertainty around the estimate of horizontal inequity. The reason being that the need-standardised allocation is based on the difference between the actual and the need-predicted allocation; the latter being derived from the predicted values of a regression model. Therefore, in order to account for this additional uncertainty, we use bootstrapping techniques including the model estimation used to derive the need-predicted allocation into the bootstrapping process. This approach yields to larger standard errors than those derived using the standard approach.

Chapter 4 presented the review of the empirical literature on vertical equity to identify the most comprehensive techniques and methodological gaps in the measurement of vertical inequity. No previous review has been published that covers vertical equity in health care delivery, and so this chapter provided the first review on this topic. We found that the measurement methods of vertical equity employed to date in the literature do not only differ by the specific metrics or measures analysts have used in their studies; but also by the general approach and by the assumptions underpinning their analyses. We undertook a critique of the approaches taken in the literature. The conditions highlighted by Gravelle *et al.*, 2006 when considering the main challenges of health care inequity analysis were used as a vehicle for the assessment of the existing methods. The authors of this paper identified the issues of the distinction between need and non-need variables; the omitted variable problem; and disentangling horizontal and vertical equity as the main challenges of empirical research in equity. For the specific case of accounting for vertical inequity, defining the target effect of the need indicators on health care consumption was believed to be one of the main difficulties.

We concluded that none of the measures used to date in the literature of vertical equity in health care delivery were capable of adequately meeting the highlighted challenges. In addition we try and explore the literature on the measurement of vertical inequity in other fields. None of the approaches employed in other areas were considered to provide any advantage over the methods already been used or proposed in the context of vertical equity in health care. The most comprehensive approach was provided by Sutton, 2002, which focused on the socioeconomic dimension of vertical inequity. Two main areas of further work were identified from the review of the literature. First, to extend the existing methodology proposed by Sutton to ensure that the consequences across the need distribution are fully accounted for in vertical equity analyses. And, secondly, to explore alternative ways of estimating the target (or vertically equitable) effect of the need variables in the allocation of health care. Therefore, the findings from Chapter 4 set the scene for the analyses conducted in Chapter 5 to 7.

Having identified the most comprehensive methodology proposed to date in the literature we then illustrated these methods in the context of analysing socioeconomic-related vertical and horizontal inequity in health care utilisation among individuals with cardiovascular diseases (CVD) in Chapter 5. We chose to focus on a disease-specific analysis of inequity in health care utilisation in order to allow for a more comprehensive measurement of needs for health care treatment. The main outcome of Chapter 5 is that concentrating solely on the standard horizontal inequity assessment offers only a partial view of the extent of income-related inequity in health care use. Our findings suggest that including income-related vertical inequity estimates may lead us to draw different conclusions about the nature and extent of socioeconomic inequities in health service use. After accounting for vertical inequity, we found some evidence of inequity favouring the rich for doctor visits and inpatient visits, while the horizontal inequity estimates were in both cases non-significant. Practice nurse visits were found to be horizontally pro-poor, but after accounting for vertical inequity, the estimates of income-related total inequity showed an equitable distribution across income groups. The size of the estimates of total income-related inequity that accounted for vertical inequity aspects in outpatient visit, ECG tests and heart surgery were in some cases double the size of the original estimates of horizontal inequity.

As previously highlighted, estimating the optimal effect of needs on health care delivery was found to be an area that required more attention. In Chapter 5 we explored alternative ways of estimating the target variation of health care across need groups which differed from that proposed in the literature. Sutton, 2002, derived the target allocation by imposing the negative linear effect of health on use found in one part of the health distribution (among the healthy) on to respondents across the whole health distribution. This imposed the restriction that the relationship between changes in health and changes in use among the unhealthy ought to be the same as this relationship among the healthy. Furthermore, the underlying requirement for choosing this target was that the effect of the health variable ought to be negative across the full range of the health distribution. As informed from the findings of Chapter 3, the imposition of a strictly negative effect of health on utilisation may not be appropriate for specific types of services or patients. Therefore, we adopted a different approach. Our method was based on identifying sub-groups of respondents who have been shown in previous studies to be less likely to be affected by unmet health care needs. Our selection of the 'target groups' was thus based on the idea that there are systematic unmet needs for some groups of the population, and therefore the estimated effect of needs on health care may be biased downward in these groups. Evidence indicates that individuals with higher income and better educational attainments are less likely to have unmet needs for health care. We thus hypothesised that the effect of needs on health care use among these subgroups would capture the optimal variations of health care consumption for different levels of needs better than the effect estimated across the full population (i.e. including individuals with forgone health care). Our empirical findings appeared to corroborate this assumption. We found that for most types of health care utilisation the effect of the need indicators was steeper in the target groups than in the general population.

In addition to illustrating the methodology proposed by Sutton, 2002 for the measurement of vertical equity, in Chapter 5 we adjusted the methodology for the decomposition of horizontal inequity to the case of decomposing vertical equity measures. We showed how the decomposition by factors property of the concentration index can be used to disentangle the sources of the estimated vertical inequity. Finding the specific need indicators responsible of the observed vertical inequity can provide useful insights for policy design aimed to tackling these inequities.

From an estimation point of view Chapter 5 exploited the uncommonly rich data available in the Health Survey for England in order to control for unobserved reporting heterogeneity in the measure of needs; as well as to investigate potential sample selection bias resulting from individuals being unaware of their health condition due to a lack of contact with health services. Our findings suggested that after controlling for a comprehensive set of health indicators (including doctor-diagnosed conditions, anthropometrics measures of objective health, symptom-based indicators, self-reported long-standing illnesses, and comorbidities) richer, better educated, white and married individuals tend to report better health status. With respect to the sample selection problem, we found no evidence of bias resulting from the fact that individuals who are unaware and do not report to have a CVD condition might be different in unobservable ways which also affect their utilisation of health services.

An additional contribution to the investigation of income-related vertical and horizontal inequity undertaken in Chapter 5 was the inclusion of up to eight types of health care contacts and procedures in the equity analyses. This approach allowed us to examine whether or not the nature and extent of inequity was different for different types of use. We found that services commonly provided in primary care settings appeared to be equitably distributed across income groups, while outpatient visits, and specialised procedures (electrical recordings of the heart and heart surgery) were found to be disproportionately concentrated among the rich. This is an important finding as it might suggest a barrier for those with lower incomes to access secondary care. As GPs in the English NHS act as 'gatekeepers' of the health care system, our findings may reflect the fact that richer individuals may be more likely to request specialised care and be more capable of persuading GPs to be referred for specialist services. Our findings might to some extent also capture a higher private consumption of these specialised services by the rich. However, our results are consistent with previous evidence of inequity in health care utilisation in England that focused only on NHS service use (e.g. see review by Goddard *et al.*, 2001; Dixon *et al.*, 2007).

In Chapter 5 we illustrated the methods already proposed in the literature to measure vertical equity. However, these methods were proposed to take into account the socioeconomic dimension of vertical inequity alone. In Chapter 6 we further developed the methodology proposed by Sutton, 2002 to relax the condition that vertical equity strictly depends on the relationship between needs and the socioeconomic measure. We highlighted that the underpinning condition of the socioeconomic dimension analysis of vertical inequity implied that if the concentration index of needs with respect to income tends to zero, the index of income-related vertical inequity will tend to zero, independently of the size of the difference between the actual and the appropriate effect of the need indicators on use. We proposed a measure of vertical inequity that takes into account the distributional consequences of the inappropriate effect of the need variables across the whole need distribution. We accomplish this by measuring vertical inequity by a means of the concentration index with respect to the need rank rather than with respect to the socioeconomic rank.

We showed how this measure of vertical equity is necessarily equal to or larger than the income-related vertical inequity estimate when one need measure is used in the utilisation equation, and that this was also likely to hold when more need indicators are included, as demonstrated by our findings. Our proposed estimate is sensitive to the distribution of needs in the population under analysis. This property is crucial for the measurement of vertical equity as it ensures that the index would be larger in a population where individuals are more 'unequal' with respect to their needs than in a population where everyone have relatively similar needs. In the case that everyone had similar levels of needs (Gini coefficient close to zero) the estimate of vertical inequity will legitimately tend to zero, suggesting that if there are not 'unequal' individuals in the population there is not vertical inequity. We thus concluded that the need dimension allows us to appropriately quantify the extent of vertical inequity across need groups; while the use of the socioeconomic dimension proposed by Sutton, 2002 identifies only the consequences of vertical inequity across the income distribution. We recognised that the choice between these two estimates would depend on the research question at hand, but we believe our proposed measure to be capable of measuring how vertical equity is generally defined.

A second methodological outcome of our proposed approach was the implication of the inclusion of the need dimension for the analysis of horizontal inequity. We considered the standard approach of measuring horizontal inequity with respect to the socioeconomic dimension an obvious and appropriate choice. But in addition to exploring that, we illustrated how the distributional consequences of the effect of the non-need variables on health care use across need groups could be quantified. The need-related horizontal inequity index thus provides an estimation of the impact that factors which ought not to affect health care consumption have on the distribution of care across need groups. We showed that including the need dimension alongside the socioeconomic dimension in the analysis of inequity in health care delivery allows us to fully measure both vertical and horizontal inequity aspects and the consequences that each of them has on the population groups identified by the other. This condition highlighted by Gravelle, *et al.*, 2006 when considering the challenges in the quantification of inequity in health care delivery, was not appropriately met by any of the methodologies used to date in the literature.

The main finding of the empirical analyses conducted in Chapter 6 showed that the extent of income-related vertical inequity is only a fraction of the extent of the vertical inequity as measured with respect to the need dimension. The extent of vertical inequity was found much larger when the full distribution of needs was taken into account. The difference between these two estimates was mainly driven by the difference between the CI of health with respect to income and the Gini index of health. Consistent with the analyses undertaken in Chapter 2, and similarly to previous evidence, the CI was found to be around 28% of the Gini index of health. Therefore, we concluded that similar results on the relationship between need-related and income-related vertical equity as shown in our study are likely to be found elsewhere.

An additional finding from the analyses undertaken in Chapter 6 related to one assumption commonly applied to the horizontal inequity analysis. This assumption implies that unexplained variation in health care use reflects unjustifiable sources of inequity, and it is therefore considered to be horizontally inequitable. Horizontal inequity indices that include the contribution of the error term have been labelled the ‘conventional’ horizontal inequity index by Bago d’Uva *et al.*, 2009. These authors have proposed a more ‘conservative’ horizontal inequity index that excludes the contribution of the residual, on the basis that the error term may be picking up unobserved need factors. The comparison across the conventional and the conservative estimate of horizontal inequity across the need and the socioeconomic dimension can be used to shed some light onto this issue. We found some evidence in our data suggesting that the residual term may be picking up unobserved need characteristics rather than unjustifiable variations in utilisation, as its correlation was found to be generally stronger with respect to the need index than with respect to the income variable. This might suggest that the assumption underpinning the conventional approach does not hold, and therefore the estimates using the conservative approach should be preferred.

With regards the empirical findings of need-related inequity in health care utilisation among individuals with CVD, we found evidence of total inequity favouring the healthy in a number of types of health care utilisation, such as outpatient visits, ECG tests, and heart surgery, and some weak evidence for the case of doctor visits, inpatient stays and regular check-ups. These results suggest that the high needs of some individuals are being ‘squeezed’ by the less important demands of others for these particular health services (Sutton, 2002). In most cases, the magnitudes of the pro-healthy total inequity estimates were mainly driven by the size of the vertical inequity aspects of that inequity. All in all, our findings suggest that health care provision among individuals reporting CVD is generally not distributed according to needs, and the main source of these inequities lies in the inappropriate effect of the need indicators on use rather than on the impact of socioeconomic variables in the distribution of health care across need groups.

Finally, Chapter 7 provided an illustration and adaptation of the methods previously developed in this thesis for the analysis of vertical and horizontal inequity in the context of longitudinal information on area level spending on cancer across Primary Care Trusts (PCTs) in England. We investigated whether the proposed techniques developed in previous chapters could be applied to area level investigations. Inequities in area level allocations are of special interest in the English NHS given that the resource allocation formula used to distribute resources is explicitly designed to eliminate inequities in expenditure between administrative areas. The main contribution from this analysis with regards to vertical equity considerations was the use of objective indicators of performance to identify subgroups of PCTs more likely to meet the need of their population in order to estimate the target effect of need factors on spending. We used information from cancer outcomes (i.e. under 75 year-old standardised mortality ratio from cancer; and cancer survival rates), treatment and prevention patterns (screening coverage rates; compliance with 62-day treatment; two-week wait referrals; diagnosis after emergency admission rates, etc.), World Class Commissioning scores in relevant competencies (i.e. related to meeting population needs and reducing health inequalities), and information about which areas allocate more resources to needy PCTs. We found the effects of the need indicators estimated among the PCTs which met the largest numbers of the selected criteria to allocate proportionally more resources to areas with relatively larger cancer resources needs than that estimated across the full sample.

One particular challenge of working with area level data in equity analyses is that socioeconomic measures often reflect, and are used as, proxies for need indicators. In the analysis conducted in Chapter 7, we tried and included a comprehensive set of need variables that capture both the number as well as the severity of cancer cases across regions. In addition to the area demographic profiles and mortality ratios, commonly used as the single need indicators in area level investigations, we included the count of cancer cases in each PCT and derived a cancer-severity index using information from a household survey. We also exploited the longitudinal nature of our data and we used econometric techniques that facilitate the control for unobserved factors that might be correlated with the covariates in our models. We found that including these need indicators and controlling for potential unobserved factors wiped out the estimated effect of the main socioeconomic indicators included in our analysis (i.e. the effect of the number of job seekers' claimants was found significantly and positively correlated with cancer spending; but after controlling for the set of need indicators and its potential endogeneity, the coefficient became non-significant). This result highlights the importance of controlling comprehensively for needs in area level investigations of inequity where socioeconomic factors tend to pick up unobserved need characteristics.

The equity empirical results from Chapter 7 showed that in the case of socioeconomic-related inequity estimates, the inclusion of vertical inequity measured using SES ranks, in addition to horizontal inequity did not affect substantially the final conclusions about socioeconomic-related inequity in the allocation of cancer spending. However, similarly to the analysis conducted in the previous chapter, when the need indicator was used as the dimension for the measurement of inequity, the extent of vertical inequity was found to be much larger. Moreover, the inclusion of the need dimension in addition of the socioeconomic dimension in health care equity investigations provided valuable information: the main empirical findings of this chapter suggested that while cancer spending might be concentrated on more deprived areas, there is some evidence of inequity favouring healthier regions.

Taken together the analyses conducted in Chapter 2 to 7 provided a comprehensive picture of the inequality and inequity in health and health care in England. We explored in much detail the overlooked issue of vertical equity in health care delivery. Our findings suggest that there is vertical inequity in the delivery of health care in England; i.e., there is not appropriately unequal treatment for unequal needs. In our analyses, vertical inequity appeared in some cases to disfavour the more economically deprived, but the consequences of the observed vertical inequities on the distribution of health care across need groups were found to be more pronounced and in detriment to those with larger needs. Bearing these points in mind we now discuss some policy and research implications of the analyses.

8.3. Policy and research implications

We discuss some of the implications from the findings of the analyses conducted in this thesis for policy design. We then move to highlight the main implications for the research conducted in the area of inequity in the delivery of health care and outline some recommendations.

8.3.1. Policy implications

We consider three areas of policy implications: i) addressing vertical inequity in health care delivery in order to close the health gap; ii) the emphasis on the need dimension in addition to the socioeconomic dimension when designing policies aimed to tackling inequities in health and health care delivery; and iii) the barriers to services provided in secondary care.

Addressing vertical inequity in the distribution of health care resources

In this thesis we have provided evidence of the existing vertical inequity in the English health care system. As we noted at the outset, considerations of vertical inequities have been highlighted as a means to achieve the Government aim of reducing avoidable inequalities in health in England. Therefore, our findings emphasise the need to address vertical inequity in the provision of health care if the gap in health status across individuals in the population is to be reduced.

The commitment to ensure that vertical inequities are addressed would imply that more efforts need to be made in order to achieve the appropriate variation in care provided to individuals with different levels of needs. In general, incorporating vertical inequity aspects in the policy design would involve selecting the relevant attributes or 'need indicators' that ought to affect the allocation, and estimating the vertically equitable magnitude of the variation in resources across different levels of needs. One area where addressing vertical inequity would be necessarily is related with the way health care resources are geographically allocated across areas in England. As already discussed, the vertical equity criterion is not currently explicitly included in the design of the formula used to geographically distribute NHS resources. This implies that policies would need to pay more attention to the way health care resources vary with variations in need levels, and should aim at allocating resources according to the optimal variation rather than to the actual variation currently observed between health care consumption and needs.

There might be different approaches to this end; we briefly summarise some of them. Work from Mooney and colleagues in Australia have largely build onto the idea that society might want to give preference, on vertical equity grounds, to health gains of groups which are in average in poor health, such as the poor, Aborigines, etc. Therefore, they suggest asking the community what constitute claims (attributes) and what the relative strengths of different claims (weights) are. In a very similar line, but within a slightly different context, Dolan *et al.*, 2008 have tried to elicit the relevant attributes and the weights that the general public think should apply to macro level resource allocation decisions. This evaluation was undertaken to inform whether health benefits as defined by Quality-Adjusted Life Years (QALYs) should have the same weight regardless of who gets them in cost-effectiveness analyses used to make health technology coverage decisions in the UK. They found that the time of illness (children versus adults), the severity of illness, and the responsibility for the illness to be relevant factors in resource allocation decision making based on the results from a focus group of 57 members of the public and 172 NHS employees.

In recent reviews of the need component of the formula, both in the AREA report (Sutton *et al.*, 2002) and in the CARAN report (Morris *et al.*, 2007), there have been attempts to account for vertical equity in the resource allocation formula. The approach considered rested on the idea that within a country, some areas might be more ‘responsive’ to the needs of their populations, and therefore the authors suggest using the effect estimated among the areas which allocate more resources to needy regions. Sutton and Lock, 2000 proposed to go further and suggested an extra adjustment to achieve that the differential level of health care resources received by high- and low-need small areas nationally to be the same as in the most progressive area. This adjustment implied to address for the within-area allocation of resources. In a critical review of the ‘health inequality adjustment’ incorporated in recent years in the resource allocation formulae, Morris *et al.*, 2010 proposed the use of external evidence as provided by the World Class Commissioning (WCC) framework to identify PTCs able to optimally align variations in resource use with variations in needs. Further research about the suitability of the WCC framework for this purpose was recommended.

Finally, some authors in the UK have advocated for a complete departure from the way resources are geographically allocated in England. Currently, the needs component of the formulae is based on an utilisation approach. This assumes that expenditure on NHS activity in different geographical areas reflects relative needs and supply conditions, and that these can be disentangled by regression models to yield an estimate of relative need. These assumptions have been challenged on the grounds that the needs of some groups may be systematically 'unmet'. Therefore, this criticism is in line with the fact that the recovered coefficients of the need variables in the utilisation equations might not be appropriate. An alternative approach has been suggested based on variations in the prevalence of health conditions, called the 'epidemiological approach'. The epidemiological approach uses direct measures of morbidity to allocate health care resources. It divides the total national budget into disease programmes based on primary diagnosis, computes the proportion of total cases for each programme in each geographical area, and then allocates budgets to geographical areas proportional to their share of total cases. However, if no account is made for variations in the severity of cases across areas, this approach would fail to provide a vertically equitable health care distribution. The reason is that the underpinning assumption of the epidemiological approach (named the proportionally assumption) requires that the average level of need for 'cases' within each disease programme is the same in every area. Recent work has shown regional variation in disease severity for major diseases, which suggest that health care needs for some conditions vary by area (Vallejo-Torres *et al.*, 2009).

Considering inequities in the distribution of health care across need groups

A critical component of inequity analyses is to select the dimensions across which there are inequities concerns. This issue has traditionally been taken for granted on empirical inequity analyses of the delivery of health care, which have focused in most cases on deviations of inequity principles with respect to the socioeconomic dimension. In this thesis we have shown that incorporating the need dimension into the analysis of inequity in health care delivery has unmasked vertical inequities in the provision of health care that would otherwise not being captured by looking only at the socioeconomic dimension.

The traditional focus on investigating variations in the provision of health care across socioeconomic groups lies on the belief that some inequities might be considered less fair than others. While this argument might be considered relatively straightforward when the comparison is between overall inequalities in health and socioeconomic inequalities in health, it is less so in the case of need-related versus socioeconomic-related inequity in health care use. The reason being that the need-related approach does not capture overall variation in health care utilisation (as the overall health inequalities approach does with respect to health), but it identifies inequities in health care provision across individuals with different levels of needs. Therefore, society might consider inequities that are in detriment to those with larger needs to be even more unfair than those which are in detriment to those with lower incomes. An example are the preliminary findings from a study which tries to identify relevant issues for health care resources prioritisation considered by the general public (Donaldson *et al.*, 2008). When individuals were asked to rank attributes according to their importance, the 'social class of the patient typically affected' ranked last, on average, over the ten attributes considered (while quality of life before treatment ranked first). Therefore, these findings together with the work from Dolan *et al.*, 2008 mentioned above, show a primary concern on the health status of individuals when making resource allocation decisions.

While the focus on the need dimension might be a departure from the way inequities in the distribution of health care are traditionally measured in empirical studies, in terms of policy implications it simply implies that efforts and resources should be targeted to improve the health outcomes of those whose health is worst, however poor or rich these individuals happen to be. This objective does not appear to be a departure from the actual principles underpinning the distribution of health care in England. However, as inequities which arise due to variations in socioeconomic circumstances are generally seen to be an infringement of social justice, many policies have been designed to target individuals and/or areas in particularly socioeconomically deprived groups. While these policies are in line with the target of contributing to reduce the undesirable social gradient observed in health, more attention needs to be paid so individuals with higher needs, wherever they might be in the socioeconomic scale, receive the care they need. A potential consequence of the focus on the socioeconomic dimension was provided in Chapter 7, when we found that while cancer spending might be concentrated on poorer areas, the distribution also appeared to favour areas with lower needs. Therefore while one might agree with the focus on the socioeconomic dimension when analysing inequity in the delivery of health care, policy makers should not lose sight of inequities in health care provision across need groups if the aim of distributing health care according to 'needs' is to be met.

Breaking down the barriers for specialised care

Related to the common concern on socioeconomic-related inequity, in Chapter 5 we found that individuals who are better off in terms of having higher incomes and better educational attainments appeared to benefit from more 'responsive' health care treatment, in the sense that better-off individuals appear to received more health care when they have high needs as compared with the general population. This was found to be particularly the case for services provided in secondary care. In the UK, access to specialised services is controlled by GPs; therefore, this finding might suggest the difficulty for certain groups of the population to 'pass through the gate'.

Similar results have been found in terms of horizontal inequity in specialised care in previous studies, both in 'macro studies' which have looked at use of care for any cause after adjusting for broad need measures, and 'micro studies' which have looked at specific services adjusting for disease-specific need indicators (Dixon *et al.*, 2007). While pro-rich horizontal inequities in specialised care indicate that for equal level of needs, richer individuals tend to have more use of specialised procedures and specialist doctor visits; our findings in terms of vertical inequity suggest that worse off individuals do not receive as much more treatment when they need it as other individuals in better off socioeconomic status. Therefore, not only do richer groups receive more specialised care, all else equal, but also they are more appropriately prioritised in the allocation of health care according to their need levels.

These findings imply that one of the main challenges for the design of policies that aim to provide an equitable provision of health care services across social groups continue to be breaking down the barriers to the appropriate utilisation of secondary care services. As the analysis of the need dimension conducted in Chapter 6 in this thesis highlighted, the existing inequities are also in detriment to individuals with lower health status, who are not appropriately accessing the treatment they need.

8.3.2. Research implications

We now briefly highlight the main implications, and outline some recommendations, for future research that focuses on investigating inequalities in health care delivery.

Incorporating vertical equity considerations to the analysis of socioeconomic inequity

The vast majority of economic analyses of equity in the delivery of health care have focused solely on considerations of horizontal inequity with respect to the socioeconomic dimension. Our findings have emphasised that analyses that aim at exploring inequities the provision of health care across socioeconomic groups and consider only horizontal inequity offer only a partial assessment of the potential unfair variation in health care allocation across rich and poor groups. Therefore, we recommend incorporating socioeconomic-related vertical inequity considerations into the analyses of socioeconomic related inequity in health care delivery in order to make more robust claims about the extent to which variations in the provision of health care across socioeconomic groups are equitable.

Considering the need dimension for the analysis of vertical inequity

Furthermore, we show that in order to measure vertical inequity in the delivery of health care, the focus on the socioeconomic dimension is only capable of picking up part of the extent to which individuals with different needs do not receive appropriately different care across the need distribution. We recommend that for the quantification of vertical inequity, the analysis should incorporate the full variation in health care allocation across needs groups, and not only variations which are socioeconomically patterned. We believe this approach reflects vertical inequity as it is generally defined.

Identifying subgroups not affected by unmet needs to estimate target effect of need indicators on use

In order to measure vertical equity, one of the main identified challenges was to define the appropriate effect of the need indicators on the health care provision. Previous research have focused on identifying the spectrum of the health distribution where the effect of health on use was strictly negative, and thus have drawn a target subsample based only on one part of the health distribution. We challenged the imposition that the effect of health on use ought to be negative across the full distribution of needs, as strictly increasing amounts of care with lower health status might not be appropriate for specific types of services and/or patients. We propose to select target groups drawn across the full spectrum of the health distribution, and based the identification of these subgroups on external evidence about groups the population more likely to reflect a vertically equitable variation in health care with variation in needs. We also suggest undertaking a sensitivity analysis with alternative targets to investigate the robustness of the results.

Incorporating uncertainty due to model estimation into the statistical inference of equity estimates

In addition to implications directly related with the analysis of vertical inequity, some side issues for equity research were also identified. With respect to the statistical inference of equity estimates, most empirical research that measure horizontal inequity in the delivery of health care has inferred the statistical significance of the horizontal inequity estimates based on the standard errors around the concentration index of the need-standardised health care allocation. However, this approach ignores the uncertainty incorporated by the fact that the need-standardised variable is derived from the predicted values of a regression model of health care utilisation. Therefore, we propose to use bootstrapping techniques including the model estimation within the bootstrapping process to capture this source of extra uncertainty in the computation of the standard errors around the equity estimates.

Exploring the assumption about the contribution of the error term to inequality

In the analyses conducted in this thesis we also found some evidence indicating that one common assumption underpinning horizontal inequity investigations might not hold. This centre on the assumption that the contribution of the error term reflects unjustifiable sources of inequality in health care, and that it should thus be incorporated into the estimate of horizontal inequity. We found that the contribution of the error term was very strongly and positively correlated with our need measure. This might suggest that the assumption underpinning the conventional approach does not hold, and therefore the estimates of horizontal inequity which do not include the contribution of the error term might be preferred. We suggest that future studies should assess the correlation of the error term with their needs and with their non-need measures using similar methods as proposed in this thesis to draw their own conclusions about the role of the contribution of the error term to the estimated inequality.

Considering alternative health care contacts and allowing for potential correlation

We have also highlighted the importance of considering alternative health care contacts when estimating the inequity in the provision of health care within a service, such as primary care, or for particular groups of individuals, such as those suffering from cardiovascular diseases. In order to draw a full picture of inequity in health care provision, we therefore recommend accounting for the various types of services that individuals may receive. Furthermore, when allowing for these types of care to be correlated, we found significant correlation between particular types of services which indicates that simultaneous equations techniques that allow for unobserved correlation are more appropriate that models which assume the equations to be independent.

8.4. Some shortcoming and issues for further research

The main finding of this thesis is that there is vertical inequity in the delivery of health care in England in detriment to socioeconomic deprived groups and, to a larger extent, in detriment to those with worst health. While for the reasons discussed above this is an interesting finding with important research and policy implications it is acknowledged that there are a number of limitations. These arise mainly from the restrictions in the available data. We discuss these restrictions and suggest areas for further research.

8.4.1. Measures of need for health care

Ideally, measures of capacity to benefit from health care services should be used as indicators of need for health care. However that data is in most cases not available and therefore capacity to benefit is commonly proxied by health indicators, assuming that lower levels of health are related with higher capacity to benefit from using health care. In our analysis we have taken this approach and used indicators of morbidity and severity to generate indices of needs for health care. In the context of the area level analysis, the issue of appropriately capturing variation in needs in different populations was even more challenging. We tried and included a list of indicators aimed to capture the number of cases as well as the severity of the cases; however, unobserved need variation is still expected to remain in our analyses.

The difficulty of measuring needs has led us to select the approach of limiting our inequity analyses to specific disease areas separately. We believe this approach to facilitate the use of more appropriate measures of needs capable to explain variation in disease-specific health care provision. A larger and more comprehensive set of health measures was available and included in our analyses compared to that included in the majority of previous research to date. However, this approach comes to the price of losing the system-wide perspective which has been the focus of most previous work in the literature.

If the system-wide perspective is to be taken in order to make general conclusions about the inequity in a system as a whole, more work is needed in order to provide more appropriate measures of needs. The omitted variable problem mentioned in this thesis implies that the effect of socioeconomic variables included in the regression analyses may be contaminated due to correlation with unobserved need characteristics. In that case, conclusions about the estimated inequity in a system would be biased, which might generally tend to underestimate the inequity in a system. In the absence of comprehensive measures of needs, which is commonly the case in analyses in the literature, econometrics techniques that aim to account for potential endogeneity problems might be used to minimise this source of bias. These techniques can also facilitate addressing a common limitation of the use of health status measures already discussed in this thesis, i.e. the potential of reverse causality between health care utilisation and indicators of health.

8.4.2. Measures of health care delivery

Measures of health care delivery are often simple indicators of use that ignore quality of provision. In the case of our individual level analyses, we measured health care provision crudely as binary variables indicating the probability of having each of the considered contacts and procedures during the, in some cases very short, time period under analysis. One obvious limitation is that we cannot assume that all visits have the same quality.

The upshot is that it would be useful and informative to analyse inequities in the quality of care provided to different individuals as those might exacerbate inequities in quantity (van

Doorslaer *et al.*, 2006). Such analyses would require detailed information of quality indicators in the provision of health care. Some potential sources of data are the information currently being collected within the Quality and Outcome Framework (QOF). QOF is a major recent initiative which rewards achievements on a set of quality indicators for targeted chronic diseases in primary care, and thus collects information on a series of quality indicators. Also the English Longitudinal Survey of Aging (ELSA) provides data from a representative sample of adults aged 50 and over, and in recent waves provides information from 32 indicators of quality of care. Therefore, it might be possible and interesting to address this issue in the future.

8.4.3. Estimating the target effect of the need indicators

Finding the way in which health care consumption ought to vary at different levels of needs is probably the main challenge of vertical inequity investigations. In the absence of information on the policy maker's or societal notion about how much more 'needy' individual ought to receive compared to those with lower needs, we have tried to estimate this optimal variation based on external evidence. In the case of the individual level analyses, we estimated the effect among subgroups of the population found in the literature to be less likely to be affected by unmet needs. In the area level examination we used a list of performance indicators to identify PCTs able to align variation in resources with variations in needs among their populations.

Although we offer a theoretical justification and our findings corroborate our approach, the choice of our targets remains unavoidably subjective, and some might consider them to be arbitrary. However, we argue that the use of the national average estimates might also be judged to be an arbitrary choice, and we believe that our approach, although probably not completely satisfactory, does provide an advantage over the standard assumption that '*on average the system gets it right'*.

Interestingly, there are other areas in which the use of the national average as the norm is being questioned. Some people have heavily criticised the use of cost data averaged across all NHS Trusts to form the basis for calculating the tariff used in the payment system (Payment by Results) that governs transactions between commissioners and acute hospital providers. An alternative approach has been considered which involves setting tariff prices normatively, i.e. what the cost should be if best practice is followed rather than the national average of reference costs (Department of Health, 2010). A similar approach could be taken to assess how much care should be provided and/or how much resources should be spent, for a given budget, if best practice and clinical guidelines are followed in the provision of health care across individuals with different needs. This would not be a straightforward task, especially in the context of studies looking at inequity in broadly defined health care service measures. Nonetheless it would be an important step forward in determining the appropriate variation in health care consumption with variation in need factors.

8.4.4. Combining SES-related horizontal inequity and need-related vertical inequity

We have proposed in this thesis to focus on the need dimension for a full assessment of vertical inequity across need groups in a population. However, we recognise that the standard approach of measuring horizontal inequity by accounting for systematic variations across socioeconomic groups in the care provided to individual with the same needs to be an obvious and appropriate choice. By measuring separately both horizontal and vertical inequity with respect to the need dimension and with respect to the SES dimension we are capable of measuring both vertical and horizontal inequity aspects and the consequences that each of them has on the population groups identified by the other. However, a methodological limitation for the measurement of inequity in the delivery of health care of the techniques discussed and proposed in this thesis is that the measure of need-related vertical inequity and the measure of socioeconomic-related horizontal inequity cannot be combined into a single index.

These analyses can thus only be conducted separately. Appropriately defining the research question under consideration should drive the choice of the dimension for the analysis of inequity in the delivery of health care. Further work to identified ways of linking the estimates of socioeconomic-related horizontal inequity with the estimates of need-related vertical inequity would be worthwhile.

8.5. What does this thesis add?

The aim of this thesis has been to provide a rigorous and quantitative analysis of vertical equity in the delivery of health care. We aimed at assessing and refining the existing methodology for the quantification of vertical inequity in the delivery of health care, and to offer evidence about the vertical inequity in the English health care system. To meet these aims we conducted a review of the literature on vertical equity; we extended the most comprehensive techniques proposed to date to address the methodological gaps identified; and we applied our proposed methodology to different sets of data covering the contexts in which inequities in health care delivery are commonly investigated, i.e. in individual level utilisation of health care services and in area level allocations of health care resources.

The thesis makes an original contribution to the literature in four major respects. First, we conducted a review of the literature on vertical equity in the delivery of health care as well as in other fields for the first time. Second, we showed that by focusing on the need dimension in the analysis of vertical inequity we are capable of capturing the extent to which individuals with different needs do not receive appropriately different treatment across the full need distribution, and that this is likely to show a larger degree of inequity than when the focus is on the consequences of vertical inequity across socioeconomic groups. Thirdly, we demonstrated that by including the need dimension alongside the socioeconomic dimension in the analysis of inequity in health care delivery we are capable of measuring both vertical and horizontal inequity aspects and the consequences that each of them has on the population groups identified by the other. This condition highlighted by Gravelle *et al*., 2006 when considering the challenges in the quantification of inequity in health care delivery, was not appropriately met by any of the methodologies used to date in the literature. The fourth original contribution is in terms of the empirical findings with respect to inequity in health service delivery, once we account for vertical inequity. We found that including vertical inequity estimates may lead us to draw different conclusions about the nature and extent of inequity in health service use. Given the large and international body of research that have grown up around the issue of inequities in health care delivery and that currently ignore vertical inequity considerations, this finding is of considerable relevance. Conclusions about the existence of inequity in the provision of health care are therefore extensively being made on the basis of incomplete information.

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APPENDICES

Appendices to Chapter 2

Appendix 2.1. Main results using actual EQ-5D values

	Health	Income	CCI	CGini	N
National					
2004-2006	0.871	£29,615	0.1222	0.3744	20,943
North East					
2004-2006	0.825	£23,926	0.1520	0.4922	1,243
North West					
2004-2006	0.862	£27,660	0.1340	0.4009	2,885
West Midlands					
2004-2006	0.860	£26,431	0.1330	0.3993	2,297
Yorkshire					
2004-2006	0.863	£27,003	0.1316	0.3977	2,266
East Midlands					
2004-2006	0.868	£26,867	0.1030	0.3800	1,917
London					
2004-2006	0.886	£34,176	0.1166	0.3465	2,007
East of England					
2004-2006	0.881	£31,206	0.1066	0.3455	2,598
South East					
2004-2006	0.887	£34,408	0.1158	0.3325	3,622
South West					
2004-2006	0.880	£28,451	0.0879	0.3491	2,108

Note: CCI = corrected concentration index; CGini = corrected Gini index.

All indices are statistically significantly different from zero

Appendix 2.2. Main results including observations with imputed income

	Health	Income	CCI	CGini	N
National					
1998-2000	0.846	£20,550	0.1089	0.3491	31,567
2001-2003	0.852	£25,201	0.1164	0.3428	37,589
2004-2006	0.860	£28,144	0.1088	0.3325	28,374
All years	0.853	£24,583	0.1113	0.3417	97,539
North East					
1998-2000	0.808	£15,506	0.1269	0.4300	1,847
2001-2003	0.820	£21,308	0.1238	0.4138	2,336
2004-2006	0.822	£23,019	0.1356	0.4157	1,627
All years	0.817	£20,024	0.1289	0.4195	5,809
North West					
1998-2000	0.833	£18,724	0.1150	0.3832	4,391
2001-2003	0.835	£22,467	0.1284	0.3802	5,260
2004-2006	0.847	£26,374	0.1164	0.3629	3,933
All years	0.838	£22,762	0.1204	0.3761	13,594
West midlands					
1998-2000	0.838	£17,518	0.1217	0.3673	3,428
2001-2003	0.842	£22,424	0.1365	0.3679	4,061
2004-2006	0.848	£25,036	0.1230	0.3560	3,065
All years	0.843	£21,736	0.1262	0.3635	10,549
Yorkshire					
1998-2000	0.838	£18,199	0.1026	0.3673	3,441
2001-2003	0.843	£21,562	0.1167	0.3648	3,807
2004-2006	0.849	£26,178	0.1179	0.3612	3,014
All years	0.843	£21,863	0.1131	0.3650	10,275
East Midlands					
1998-2000	0.843	£17,882	0.1064	0.3571	2,913
2001-2003	0.842	£23,083	0.1207	0.3561	3,576
2004-2006	0.855	£25,488	0.1046	0.3366	2,747
All years	0.846	£22,238	0.1094	0.3508	9,235
London					
1998-2000	0.850	£24,317	0.1030	0.3381	3,730
2001-2003	0.865	£29,565	0.1050	0.3102	4,521
2004-2006	0.880	£30,979	0.0947	0.2940	3,245
All years	0.866	£28,551	0.1042	0.3150	11,478
East of England					
1998-2000	0.864	£23,089	0.0941	0.3135	3,621
2001-2003	0.869	£27,818	0.0992	0.3052	4,364
2004-2006	0.868	£30,157	0.0978	0.3087	3,142
All years	0.867	£27,059	0.0967	0.3088	11,136
South East					
1998-2000	0.861	£25,132	0.0935	0.3048	4,777
2001-2003	0.867	£31,105	0.0953	0.3023	5,812
2004-2006	0.875	£32,962	0.1001	0.2965	4,735
All years	0.868	£29,980	0.0967	0.3016	15,325
South West					
1998-2000	0.858	£19,829	0.0861	0.3176	3,306
2001-2003	0.862	£23,039	0.0938	0.3236	3,864
2004-2006	0.867	£27,767	0.0690	0.3102	2,805
All years	0.862	£23,469	0.0831	0.3180	9,971

Note: CCI = corrected concentration index; CGini = corrected Gini index.

All indices are statistically significantly different from zero

Appendix 2.3. OLS model of health status and decomposition of the concentration index and Gini coefficient (full results)

	Regression model			Decomposition CCI					Decomposition CGini				
	Mean	Coeff	z	CI	Cont	z*	Percent	%	CI	Cont	z*	Percent	%
Age and gender													
Age	0.473	-0.307	-3.54	-0.039	0.0227	3.04	19.93		-0.103	0.05950	3.61	17.58	
Female	0.532	0.008	0.54	-0.039	-0.0007	-0.51	-0.58		-0.051	-0.00083	-0.55	-0.25	
Age-squared	0.257	0.022	0.11	-0.087	-0.0020	-0.10	-1.74		-0.191	-0.00426	-0.11	-1.26	
Age-cubed	0.155	-0.036	-0.27	-0.134	0.0031	0.25	2.72		-0.263	0.00584	0.27	1.73	
Female*age	0.253	-0.078	-0.73	-0.078	0.0064	0.67	5.61		-0.160	0.01254	0.74	3.71	
Female*age-squared	0.139	0.117	0.49	-0.125	-0.0086	-0.46	-7.56		-0.253	-0.01645	-0.49	-4.86	
Female*age-cubed	0.084	-0.097	-0.59	-0.171	0.0060	0.56	5.27	23.6	-0.327	0.01072	0.59	3.17	19.8
Log household income	9.834	0.023	21.41	0.045	0.0403	22.12	35.34	35.3	0.012	0.01063	17.00	3.14	3.1
Social class of head of household													
Professional	0.072	Base Category											
Managerial/technical	0.330	-0.001	-0.62	0.305	-0.0005	-0.62	-0.43		0.084	-0.00014	-0.62	-0.04	
Skilled non-manual	0.145	0.002	0.69	-0.088	-0.0001	-0.68	-0.08		-0.031	-0.00003	-0.65	-0.01	
Skilled manual	0.250	-0.004	-1.51	-0.159	0.0006	1.50	0.50		-0.022	0.00008	1.25	0.02	
Semi-skilled manual	0.135	-0.006	-2.16	-0.333	0.0011	2.29	0.99		-0.111	0.00036	1.95	0.11	
Unskilled manual	0.045	-0.008	-1.95	-0.438	0.0007	1.91	0.57		-0.205	0.00030	1.74	0.09	
Other	0.023	-0.010	-2.05	-0.332	0.0004	1.99	0.32	1.9	-0.116	0.00011	1.73	0.03	0.2
Education													
Degree	0.167	Base Category											
Higher education less than degree	0.113	-0.001	-0.66	0.192	-0.0001	-0.67	-0.09		0.066	-0.00004	-0.70	-0.01	
A level or equivalent	0.122	-0.006	-3.02	0.151	-0.0004	-3.05	-0.35		0.173	-0.00048	-3.33	-0.14	
GCSE or equivalent	0.234	0.000	-0.22	0.003	0.0000	-0.08	0.00		0.104	-0.00004	-0.22	-0.01	
CSE or equivalent	0.053	-0.005	-1.89	-0.229	0.0003	1.83	0.23		0.003	0.00000	-0.27	0.00	
Other qualification	0.036	-0.003	-0.74	-0.150	0.0001	0.70	0.05		-0.185	0.00007	0.74	0.02	
No qualification	0.273	-0.024	-10.56	-0.331	0.0091	10.52	7.97	7.8	-0.273	0.00701	9.48	2.07	1.9
Ethnic group													
White	0.929	Base Category											
Black Caribbean	0.011	-0.004	-0.57	-0.216	0.0000	0.59	0.03		-0.028	0.00000	0.31	0.00	
Black African	0.008	0.031	4.88	-0.206	-0.0002	-3.70	-0.19		0.156	0.00016	2.58	0.05	
Indian	0.016	-0.017	-3.36	-0.056	0.0001	1.70	0.06		0.082	-0.00009	-4.01	-0.03	
Pakistani	0.009	-0.023	-3.03	-0.327	0.0003	3.02	0.29		0.007	-0.00001	-0.29	0.00	
Bangladeshi	0.003	-0.016	-1.41	-0.471	0.0001	1.19	0.11		0.004	0.00000	-0.06	0.00	

Chinese	0.002	0.024	2.85	0.068	0.0000	1.30	0.02		0.250	0.00005	2.03	0.02	
Other	0.016	-0.016	-3.09	-0.055	0.0001	1.91	0.05	0.4	0.050	-0.00005	-3.12	-0.01	0.0
Marital status													
Married	0.558	Base Category											
Single	0.252	-0.014	-8.11	0.007	-0.0001	-1.42	-0.09		0.204	-0.00292	-8.84	-0.86	
Separated	0.022	-0.027	-6.27	-0.139	0.0003	5.05	0.29		-0.099	0.00024	3.51	0.07	
Divorced	0.073	-0.026	-9.87	-0.100	0.0008	6.96	0.66		-0.125	0.00096	6.81	0.28	
Widowed	0.084	-0.010	-3.54	-0.272	0.0010	3.42	0.86	1.7	-0.401	0.00139	3.52	0.41	-0.1
Tenure													
Own	0.276	Base Category											
Mortgage	0.461	-0.007	-4.00	0.260	-0.0032	-3.87	-2.85		0.175	-0.00230	-4.14	-0.68	
Part mortgage	0.005	-0.024	-2.59	-0.213	0.0001	2.22	0.08		-0.011	0.00001	0.26	0.00	
Rent	0.249	-0.040	-18.23	-0.384	0.0151	17.35	13.21		-0.124	0.00490	12.37	1.45	
Free rent	0.009	-0.015	-2.20	-0.155	0.0001	1.78	0.08	10.5	-0.086	0.00005	1.41	0.01	0.8
Lifestyle													
Smoking	0.253	-0.022	-15.31	-0.121	0.0027	13.62	2.33		-0.030	0.00067	5.30	0.20	
Obesity	0.199	-0.031	-20.30	-0.055	0.0014	10.23	1.17	3.5	-0.112	0.00276	12.36	0.82	1.0
Area													
London	0.118	Base Category											
North East	0.061	-0.024	-7.19	-0.189	0.0011	5.79	0.96		-0.092	0.00055	4.12	0.16	
North West	0.135	-0.014	-5.50	-0.056	0.0004	3.98	0.39		-0.025	0.00019	2.63	0.06	
Yorkshire	0.102	-0.009	-3.27	-0.072	0.0003	2.80	0.23		-0.021	0.00008	1.65	0.02	
East Midlands	0.089	-0.014	-5.20	-0.047	0.0003	2.93	0.22		-0.021	0.00011	1.73	0.03	
West Midlands	0.108	-0.007	-2.58	-0.074	0.0002	2.46	0.19		-0.020	0.00006	1.55	0.02	
East of England	0.121	-0.002	-0.64	0.086	-0.0001	-0.65	-0.06		0.036	-0.00003	-0.68	-0.01	
South East	0.162	-0.004	-1.87	0.156	-0.0004	-1.94	-0.37		0.026	-0.00007	-2.02	-0.02	
South West	0.103	0.005	1.80	-0.010	0.0000	-0.69	-0.02	1.5	0.029	0.00006	1.46	0.02	0.3
Area characteristics													
Mean reporting very bad health	0.016	-0.447	-20.59	-0.116	0.0034	10.12	3.01		-0.094	0.003	10.05	0.81	
Mean reporting cutting down 14	0.066	-0.218	-23.89	-0.052	0.0030	9.48	2.63		-0.071	0.004	12.82	1.20	
Mean no qualifications	0.287	0.021	4.23	-0.087	-0.0021	-3.88	-1.82		-0.039	-0.001	-4.53	-0.27	
Mean white ethnic group	0.925	0.012	2.30	0.005	0.0002	2.14	0.20		-0.001	0.000	-1.58	-0.01	
Mean low income	0.192	-0.012	-2.28	-0.165	0.0015	2.24	1.33	5.4	-0.059	0.001	2.16	0.17	1.9
Year													
2006	0.148	Base Category											
2005	0.094	-0.006	-2.71	0.097	-0.0002	-0.91	-0.17		-0.002	0.00000	0.29	0.00	

2004	0.061	-0.008	-3.42	0.071	-0.0002	-1.82	-0.14		-0.021	0.00005	1.65	0.02	
2003	0.134	-0.004	-1.95	0.051	-0.0001	-0.96	-0.10		-0.078	0.00003	0.36	0.01	
2002	0.116	-0.012	-4.65	0.030	-0.0001	-4.18	-0.09		0.005	-0.00001	-0.60	0.00	
2001	0.138	-0.003	-1.28	-0.010	0.0000	0.21	0.01		-0.065	0.00036	3.36	0.11	
2000	0.094	-0.001	-0.38	-0.050	0.0000	0.24	0.01		0.044	-0.00009	-2.14	-0.03	
1999	0.070	-0.009	-3.45	-0.102	0.0003	4.61	0.25		-0.001	0.00000	0.11	0.00	
1998	0.146	-0.003	-1.44	-0.161	0.0003	3.33	0.27	0.0	0.005	-0.00001	-0.57	0.00	0.1
Missing													
Social class	0.001	0.045	3.04	0.015	0.0000	0.35	0.00		0.071	0.000	0.90	0.00	
Education	0.003	-0.036	-2.09	-0.146	0.0001	1.58	0.07		-0.145	0.000	1.37	0.02	
Ethnic group	0.002	0.032	1.91	-0.121	0.0000	-1.42	-0.04		-0.130	0.000	-1.87	-0.01	
Marital status	0.000	-0.046	-1.13	0.068	0.0000	-0.47	0.00		-0.116	0.000	0.38	0.00	
Tenure	0.000	0.013	0.44	-0.025	0.0000	-0.27	0.00		0.000	0.000	0.00	0.00	
Area	0.001	0.002	0.15	-0.166	0.0000	-0.15	0.00		-0.038	0.000	-0.06	0.00	
Obesity	0.114	-0.055	-24.27	-0.075	0.0021	9.37	1.85		-0.184	0.005	14.47	1.36	
Smoking	0.004	-0.016	-2.24	-0.155	0.0001	1.99	0.04	1.9	0.020	0.000	-0.54	0.00	1.4
Total explained								94					30
N	79,345												

Note: Coeff = Coefficient; Cont = Contribution; Percent = Percentage contribution. *Standard errors for contributor factors are derived using bootstrapping techniques. Sample weights are used and we adjust for clustering at the Primary Sample Unit level.

Appendices to Chapter 3

Appendix 3.1. Test for statistically significant differences in marginal effects on GP and practice nurse visits

	Nurse visit		GP visit		ME nurse = ME GP
	ME	t value	ME	t value	(p value)
Age & gender					
Female	-0.038	-4.28	-0.034	-2.97	p = 0.7720
Age	-1.170	-9.44	-1.638	-10.52	p = 0.0188
Age squared	2.518	8.76	3.242	8.72	p = 0.1236
Age cubed	-1.501	-7.32	-1.850	-6.79	p = 0.3056
Female*age	0.593	5.96	0.788	5.96	p = 0.2402
Female*age squared	-1.396	-5.09	-1.898	-5.08	p = 0.2795
Female*age cubed	0.885	4.17	1.185	4.04	p = 0.4065
Self-assessed general health					
Good	0.012	3.40	0.031	6.51	p = 0.0012
Fair	0.023	5.03	0.069	10.35	p < 0.0001
Bad	0.025	3.44	0.066	6.10	p = 0.0017
Very bad	0.015	1.36	0.092	5.70	p = 0.0001
Longstanding illnesses					
Neoplasms & benign growths	0.019	1.93	0.014	0.87	p = 0.7999
Endocrine & metabolic	0.040	6.65	0.045	4.76	p = 0.6484
Mental disorders	0.013	1.56	0.047	4.00	p = 0.0184
Nervous system	-0.018	-2.26	0.012	1.08	p = 0.0275
Heart & circulatory	0.029	5.41	0.034	4.19	p = 0.6501
Respiratory system	0.014	2.81	0.019	2.82	p = 0.5314
Digestive system	0.005	0.67	0.034	3.39	p = 0.0151
Genitourinary system	0.017	1.80	0.056	4.06	p = 0.0179
Skin complaints	0.012	1.45	0.047	4.21	p = 0.0127
Musculoskeletal	-0.001	-0.20	0.013	1.91	p = 0.0893
Days cutting down					
1-3 days	0.011	1.84	0.099	13.24	p < 0.0001
4-6 days	0.026	3.69	0.151	14.55	p < 0.0001
7-13 days	0.030	4.02	0.188	19.29	p < 0.0001
14 days	0.024	4.28	0.152	19.26	p < 0.0001
No of longstanding illnesses					
2	0.001	0.11	-0.014	-1.59	p = 0.1727
3	-0.016	-1.68	-0.036	-2.60	p = 0.2351
4 or more	-0.011	-0.83	-0.054	-2.68	p = 0.0772
GHQ-12 score					
1	0.006	1.26	0.022	3.18	p = 0.0553
2	0.001	0.21	0.023	2.70	p = 0.0327
3	-0.007	-0.95	0.035	3.35	p = 0.0010
4	-0.003	-0.39	0.031	2.51	p = 0.0233

5	0.001	0.09	0.050	3.79	p = 0.0027
6	-0.003	-0.28	0.056	3.99	p = 0.0007
7	0.012	1.02	0.041	2.43	p = 0.1523
8	0.009	0.68	0.086	4.90	p = 0.0004
9	0.017	1.27	0.033	1.67	p = 0.4945
10	-0.008	-0.50	0.050	2.46	p = 0.0236
11	0.023	1.49	0.066	2.93	p = 0.1113
12	0.005	0.35	0.087	3.73	p = 0.0035
Permanent sickness	0.022	2.80	-0.004	-0.29	p = 0.0833
Temporary sickness injury	0.028	1.27	0.028	0.84	p = 0.9987
Income (log)	-0.001	-0.44	-0.004	-1.64	p = 0.3246
Less than degree	0.009	1.42	0.008	0.82	p = 0.9071
Education					
A level or equivalent	0.017	2.79	0.013	1.49	p = 0.7315
GCSE or equivalent	0.009	1.54	0.019	2.42	p = 0.2956
CSE or equivalent	0.000	0.00	0.018	1.63	p = 0.1813
Other qualification	0.018	2.19	0.029	2.37	p = 0.4322
No qualification	0.005	0.92	0.020	2.33	p = 0.1651
Economic activity					
Going to school/college full time	-0.011	-1.33	-0.055	-4.82	p = 0.0024
Retired from paid work	0.004	0.60	-0.001	-0.14	p = 0.6556
Looking after the home	0.014	2.59	0.005	0.68	p = 0.3869
Waiting to take up paid job	0.017	0.57	-0.001	-0.03	p = 0.7133
Looking for paid job	0.010	0.82	-0.029	-1.72	p = 0.0597
Doing something else	0.032	1.38	-0.006	-0.16	p = 0.3788
Ethnicity					
Black Caribbean	-0.001	-0.04	0.021	1.28	p = 0.3189
Black African	0.008	0.53	0.010	0.52	p = 0.9290
Indian	-0.005	-0.39	-0.003	-0.17	p = 0.9206
Pakistani	0.005	0.38	0.064	3.68	p = 0.0057
Bangladeshi	-0.008	-0.34	0.023	0.85	p = 0.3907
Chinese	-0.047	-1.61	-0.023	-0.50	p = 0.6573
Other	-0.012	-1.09	0.025	1.93	p = 0.0293
Marital status					
Single	-0.015	-2.60	-0.026	-3.22	p = 0.2608
Separated	-0.001	-0.13	0.004	0.29	p = 0.7547
Divorced	-0.006	-1.05	0.012	1.41	p = 0.0781
Widowed	-0.008	-1.43	-0.012	-1.29	p = 0.7218
Household composition					
1 or more infants	0.008	1.56	0.025	3.40	p = 0.0648
1 children	-0.010	-2.05	0.009	1.38	p = 0.0183
2 children	-0.010	-1.81	-0.007	-0.97	p = 0.7398
3 children	-0.009	-1.14	-0.015	-1.47	p = 0.6326
4 or more	-0.015	-1.15	-0.034	-2.29	p = 0.3197
Degree of ruraliy					
Suburban	-0.010	-2.69	0.003	0.58	p = 0.0376

Urban	-0.008	-1.52	0.000	-0.03	p = 0.3649
Supply					
GP supply	0.094	2.72	0.089	2.05	p = 0.9146
Mean distance to practice	-0.005	-1.79	0.001	0.29	p = 0.1603

Appendix 3.2. Horizontal inequity indices for practice nurse and GP visits (standard errors based on standard errors around the CI of the need-standardised allocation)

CI	GP visits		Nurse visits	
	CI	t value	CI	t value
Actual use	-0.0668	-13.63	-0.0234	-6.77
Need-predicted (univariate models)	-0.0542	-34.55	-0.0244	-41.33
Need-predicted (bivariate models)	-0.0542	-34.62	-0.0246	-41.49
HI (univariate probit models)	-0.0126	-2.63	0.0010	0.29
HI (bivariate probit model)	-0.0126	-2.62	0.0011	0.33

Note: CI = concentration index; HI = horizontal inequity

Appendices to Chapter 4

Appendix 4.1. List of papers included from the main search

Abasolo, I., Manning, R. & Jones, A.M. 2001, "Equity in utilization of and access to public-sector GPs in Spain", *Applied Economics,* vol. 33, no. 3, pp. 349-364.

Alberts, J.F., Sanderman, R., Eimers, J.M. & Van Den Heuvel, W.J.A. 1997, "Socioeconomic inequity in health care: A study of services utilization in Curacao", *Social Science and Medicine,* vol. 45, no. 3, pp. 262-270.

Antioch, K.M. & Walsh, M.K. 2002, "Risk-adjusted capitation funding models for chronic disease in Australia: Alternatives to casemix funding", *European Journal of Health Economics,* vol. 3, no. 2, pp. 83-93.

Baldani, M.H., de Almeida, E.S. & Ferreira Antunes, J.L. 2009, "Equity and provision of public dental services in the State of Paraná, Southern Brazil", *Revista de saude publica,* vol. 43, no. 3, pp. 446-454.

Brownell, M.D., Roos, N.P. & Roos, L.L. 2001, "Monitoring health reform: A report card approach", *Social Science and Medicine,* vol. 52, no. 5, pp. 657-670.

Gravelle, H., Morris, S. & Sutton, M. 2006, “Economic studies of equity in the consumption of health care”, In *The Elgar Companion to Health Economics*, Jones A (ed.). Edward Elgar: Cheltenham.

Laudicella, M., Cookson, R., Jones, M.J. & Rice, N. 2009, " Health care deprivation profiles in the measurement of inequality and inequity: An application to GP fundholding in the English NHS ", *Journal of Health Economics,* in press

Liu, G.G., Zhao, Z., Cai, R., Yamada, T. & Yamada, T. 2002, "Equity in health care access to: Assessing the urban health insurance reform in China", *Social Science and Medicine,* vol. 55, no. 10, pp. 1779-1794.

Matovu, F., Goodman, C., Wiseman, V. & Mwengee, W. 2009, "How equitable is bed net ownership and utilisation in Tanzania? A practical application of the principles of horizontal and vertical equity", *Malaria Journal,* vol. 8, no. 1.

McIntyre, D. & Gilson, L. 2000, "Redressing dis-advantage: Promoting vertical equity within South Africa", *Health Care Analysis,* vol. 8, no. 3, pp. 235-258.

McIntyre, D. & Gilson, L. 2002, "Putting equity in health back onto the social policy agenda: Experience from South Africa", *Social Science and Medicine,* vol. 54, no. 11, pp. 1637-1656.

McIntyre, D., Muirhead, D. & Gilson, L. 2002, "Geographic patterns of deprivation in South Africa: Informing health equity analyses and public resource allocation strategies", *Health Policy and Planning,* vol. 17, no. SUPPL. 1, pp. 30-39.

Mooney, G. 1996, "And now for vertical equity? Some concerns arising from aboriginal health in Australia.", *Health economics,* vol. 5, no. 2, pp. 99-103.

Mooney, G. 2000, "Vertical equity in health care resource allocation", *Health Care Analysis,* vol. 8, no. 3, pp. 203-215.

Mooney, G. & Stephen, J. 1997, "Vertical equity: Weighting outcomes? Or establishing procedures?", *Health Policy,* vol. 39, no. 1, pp. 79-87.

Mooney, G., Jan, S. & Wiseman, V. 2002, "Staking a claim for claims: A case study of resource allocation in Australian Aboriginal health care", *Social Science and Medicine,* vol. 54, no. 11, pp. 1657-1667.

Mooney, G. & Henry, B. 2004, "Funding Aboriginal primary health care", *Australian Journal of Primary Health,* vol. 10, no. 3, pp. 46-53.

Raine, R. 2002, "Bias measuring bias", *Journal of Health Services Research and Policy,* vol. 7, no. 1, pp. 65-67.

Raine, R., Hutchings, A. & Black, N. 2004, "Is publicly funded health care really distributed according to need? The example of cardiac rehabilitation in the UK.", *Health policy (Amsterdam, Netherlands),* vol. 67, no. 2, pp. 227-235.

Raine, R., Goldfrad, C., Rowan, K. & Black, N. 2002, "Influence of patient gender on admission to intensive care", *Journal of Epidemiology and Community Health,* vol. 56, no. 6, pp. 418-423.

Rocha, G.M.N., Martínez, A.M.S., Ríos, E.V. & Elizondo, M.E.G. 2004, "Resource allocation equity in northeastern Mexico", *Health Policy,* vol. 70, no. 3, pp. 271-279.

Sutton, M. 2002, "Vertical and horizontal aspects of socio-economic inequity in general practitioner contacts in Scotland", *Health Economics,* vol. 11, no. 6, pp. 537-549.

Sutton, M. & Lock, P. 2000, "Regional differences in health care delivery: Implications for a national resource allocation formula", *Health Economics,* vol. 9, no. 6, pp. 547-559.

Vončina, L., Pristaš, I., Mastilica, M., Polašek, O., Šošić, Z. & Stevanović, R. 2007, "Use of preventive health care services among the unemployed in Croatia", *Croatian medical journal,* vol. 48, no. 5, pp. 667-674.

Zere, E., Moeti, M., Kirigia, J., Mwase, T. & Kataika, E. 2007, "Equity in health and healthcare in Malawi: Analysis of trends", *BMC Public Health,* vol. 7.

Appendix 4.2. Description of the studies identified in the main search

Authors	Year	Context	Aim of paper	Methods for testing for/measuring VE	VE Conclusions
			Approach 1: Association of SES and health care delivery		
Alberts JF. Sanderman R. Eimers JM. van den Heuvel WJ.	1997	Curacao, The Netherlands	To explore socioeconomic inequity in health care utilisation in Curacao, Netherlands	Unadjusted odd ratios and coefficients of education on the probability and volume of utilisation of health care	There is VI as people with higher education are more likely to use healthcare
Browell, MD., Roos NP., Roos LL.	2001	Winnipeg, Manitoba, Canada	To monitor the impact of health reform on equity and efficiency, access to care and quality of care	Standard normal theory exploring changes in relative rates of utilisation across SES groups	VE is achieved as all socioeconomic groups maintained their relative access levels
Zere, E., Moeti M., Kirigia J., Mwase T., Kataika E.	2007	Malawi, Sub-Saharan Africa	To assess trends in inequities in health status and healthcare utilisation over a period of time	Comparison of the concentration curves of health care utilisation and the concentration curve of health status with respect to wealth	There is VI as the poor experience more burden of diseases but health care is either equally distributed or distributed in favour of the non-poor
Voncina L., Pristas I., Mastilica, M., Polasek O., Sosic RS.	2007	Croatia	To explore the association between unemployment and the use of preventive health care services	Logistic regressions stratified by whether individuals are healthy or suffer from cardiovascular or metabolic disease. Look at the effect of being unemployed	There is VI as the unemployed who should be positively discriminated with the provision of health care receive less preventive interventions. This happens among healthy individuals and among those reporting cardiovascular and metabolic diseases
Baldani M.H., de Almeida E.S., Ferreira-Antunes, J.L.	2009	Paraná, Brazil	To analyse the association between SES indicators and provision of dental services and allocation of financial resources	Spearman correlation of access, utilisation and financial resources with respect to SES indices	In general, municipes with lower SES had higher access, utilisation and financial resources allocated to them which provides evidence of VE
			Approach 2: Concordance of observations with respect to need rank and health expenditure rank		

Authors	Year	Context	Aim of paper	Methods for testing for/measuring VE	VE Conclusions
Núñez-Rocha G.M., Salinas-Martinez, A.M., Villareal-Rios E., Garza-Elizondo M.E.	2004	Mexico	To measure the degree of equity in the resource allocation across areas in the north-eastern Mexico	Kendall coefficient of concordance. They compare the hierarchy of areas with respect to the health needs index, and with respect to the allocation of per capita allocation of health expenditure.	There is a low concordance between health need and allocation of health expenditure
Approach 3: Association of health indicators and health care delivery					
Abasolo I., Manning R., Jones AM.	2001	Spain	To test for horizontal and vertical equity in the utilisation and access to GP visits	In their regression analysis to test for horizontal equity, they test whether need indicators have a positive effect on use	GP utilisation are consistent with VE
Gravelle H., Morris S., Sutton M.	2001	England	To emphasises the difficulties of economic analyses of equity in consumption of health care; those are: need of value judgments, omitted variables, and identifying vertical and horizontal inequity	In their regression analysis to test for horizontal equity, they test whether need indicators have a positive effect on use	The basic test for VE is not passed for psychosocial disorders and some longstanding illnesses
Liu GG. Zhao Z. Cai R. Yamada T. Yamada T.	2002	China	To explore the impact of the health insurance reform in China on horizontal and vertical equity	Regression analysis (difference-in-differences model). By looking at the impact of having a chronic disease on the probability of different utilisation measures and compared the coefficient before and after the reform.	Chronic disease appears to be the most significant determinant of health care utilisation; and after the reform those with chronic disease were even more likely to have an outpatient visit
Matovu F., Goodman C., Wiseman V., Mwengee W.	2009	Tanga, Tanzania	To measure the extent and causes of inequalities in the ownership and utilisation of bed nets across SES groups and age groups	Regression analysis. By looking at the coefficient of being under-five on the utilisation equation	Under-five were more likely to use a net which points to VE, but the differences were relatively small

Authors	Year	Context	Aim of paper	Methods for testing for/measuring VE	VE Conclusions
Antioch KM., Walsh MK.	2002	Australia	To develop a risk-adjusted capitation funding model for cystic fibrosis for an Australian Health Maintenance Organisation	Regression analysis of cost per patient. Look at the coefficient of 'complexity' variable	Risk adjusted premium achieve greater VE through the inclusion of the 'complexity' element
Approach 4: Association of SES and health care delivery at different levels of health					
Raine R.	2002	UK	To highlight the importance of looking at vertical equity when considering the fair distribution of health care	Suggest testing for vertical equity by including interactions between non-need and need variables, or stratifying analysis according to different levels of need	No empirical work
Raine R., Hutchings A., Black N.	2004	UK	To test for vertical and horizontal inequity in the admission to cardiac rehabilitation	Regression analysis. Test for the interaction effect of age (non-need variable) and health measures in the probability of accessing rehabilitation	Males with hypertension were nearly twice as likely to undergo rehabilitation compared with females with hypertension which provides evidence of VI
Approach 5: Association of health outcomes and health care delivery across different SES					
Raine R., Goldfrad C., Rowan K., Black N.	2002	UK	To explore the casemix and mortality rates of males and females admitted to ICU to test for horizontal and vertical equity	Statistical test. By looking at whether differences in the casemix of males and females admitted to ICU was accompanied by differences in mortality risks	For some conditions, males had lower severity at admission than females, and were also less likely to die which suggest VI; in addition, for other conditions there were not differences in the casemix but one gender showed a higher mortality risk
Approach 6: Comparing actual and target effect of need indicators					

Authors	Year	Context	Aim of paper	Methods for testing for/measuring VE	VE Conclusions
Mooney G.	1996	Australia	To discuss the issue of vertical inequity using the case of aboriginal health in Australia. Discuss how vertical equity principle could be incorporated in the resources allocation formula	Suggest a potential way of incorporating the VE principle in resources allocation would be to find community weights to be applied to different health gains of different groups in a society who are on average in poor health	No empirical work
Mooney G	2000	Australia	Introduce the importance of vertical equity as a way forward to refocus on equity. They examine two possibilities of doing so; procedural justice (envy and claims) and distributive justice.	Suggest asking the community about communitarian claims; but in the short run propose asking about different weighting for health gains of different groups	Health gains of indigenous population were found to have a weight close to 3 under community preferences
Mooney G., Jan S.	1997	Australia	Examine different ways of incorporating vertical equity into health policy through distributive or procedural justice	Suggest using different weighting in the resources allocation formula for aboriginality (distributive justice), or asking the community what constitute claims and what the relative strengths of different claims are (procedural justice)	No empirical work
Mooney G., Jan S., Wiseman V.	2002	Australia	Emphases the use of 'communitarian claims' approach for resource allocation to recognise the need of Aboriginal versus non-Aboriginal populations	Suggest using different weighting in the resources allocation formula for aboriginality (distributive justice), or asking the community what constitute claims and what the relative strengths of different claims are (procedural justice)	No empirical work

Authors	Year	Context	Aim of paper	Methods for testing for/measuring VE	VE Conclusions
Mooney G., Henry B.	2004	Australia	To provide an estimate of what should be spent on aboriginal primary health care by looking at 3 elements: capacity to benefit; different weighting health gains; and incorporating Management Economic Social and Human infrastructure	Applied different weighting to aboriginals health gains by asking the community	No empirical work
McIntyre D., Gilson L.	2000	South Africa	To test for vertical equity principles in the two areas of recent policy action: public-private sector cross-subsidies and the allocation of government resources between provinces	Modify the weights of the element in the resource allocation formula, giving more weight to the element that benefit the most disadvantaged areas	Incorporating changes in the weighting of the elements would enhance the redistributive impact of the formula achieving greater vertical equity.
McIntyre D., Muirhead D., Gilson L.	2002	South Africa	Develop an area deprivation index to be used in geographical resource allocation to promote vertical equity	Small area analysis. It develop deprivation index and look at the implications of the distribution of deprivation for government resource allocation using different weighting for different elements of the formula	Including the deprivation index is negligible with the 8% weighting of the 'economic activity' component used in the current formula; when the weighting is changed, very deprived provinces see quite dramatic potential budget increases
McIntyre D., Gilson L.	2002	South Africa	To test for vertical equity principles in the health sector policies developed since 1994	Compared the allocation of resources with an adjusted allocation that removes the population already covered by insurance for 5 financial years	Resource allocation provided a useful starting point for promoting vertical equity as those provinces which were the main beneficiaries of resources redistribution were those with some of the worst health status indicators

Authors	Year	Context	Aim of paper	Methods for testing for/measuring VE	VE Conclusions
Sutton M., Lock P.	2000	Scotland	To develop a resource allocation formula using the slope of the most progressive area to measure relative needs and derive allocations	Small area analysis. It measures progressivity to spend on high need across areas, re-estimate need index using the slopes of the most progressive area and derives allocation ensuring that the differential level of health care resources received by high and low-need areas nationally is the same as achieved in the most progressive area	The locus of equity possibilities clearly illustrates that any move towards greater vertical equity necessarily involves a trade-off with geographical equity (horizontal equity in this case)
Approach 7: Health care gap between target and actual allocation of health care					
Laudicella M., Cookson R., Jones M.J, Rice N.	2009	England	Propose a new approach for the measurement of horizontal inequity in the delivery of health care based on poverty and deprivation literature	Health care deprivation profiles from the vector of health care gap between need-predicted and actual health care. Measure the impact on horizontal inequity equity on elective hip replacement of the GP fundholding reform	No empirical work on VE. The authors suggest the approach could be adjusted to account for both horizontal and vertical equity
Approach 8: Divergence of target delivery and need-predicted delivery of health care across different SES					
Sutton M.	2002	Scotland	Propose a framework for incorporating the implication of vertical inequity in the analysis of the socio-economic inequity in health care use	Concentration index. Measure vertical inequity as the divergence of the concentration of target and need-expected health use with respect to income	Found an insignificant pro-rich VI estimate, i.e. the divergence of need-predicted and target allocation of healthcare falls disproportionally on the poor

Note: VE = vertical equity; VI = vertical inequity; SES = socioeconomic status

Appendix 4.3. List of papers included from the supplementary search

Bibi, S. & Duclos, J. 2007, "Equity and policy effectiveness with imperfect targeting", *Journal of Development Economics,* vol. 83, no. 1, pp. 109-140.

Bibi, S. & Duclos, J. 2005, "Decomposing poverty changes into vertical and horizontal components", *Bulletin of Economic Research,* vol. 57, no. 2, pp. 205-215.

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Appendices to Chapter 5

Appendix 5.1. List of cardiovascular disease (CVD)-related health indicators and health care utilisation questions in the Health Survey for England

CVD-specific health indicators

- Diabetes type 1: Were you told by a doctor that you had diabetes? + How old were you when you were first told by a doctor that you had diabetes? Before 35 year-old + Do you currently inject insulin for diabetes?
- Diabetes type 2: Were you told by a doctor that you had diabetes? + otherwise
- Were you told by a doctor that you had angina?
- Were you told by a doctor that you had a stroke?
- Were you told by a doctor that you had a heart attack (including myocardial infarction or coronary thrombosis)?
- Have you ever had any pain or discomfort in your chest, in sternum (upper or middle), or sternum lower, or left anterior chest and left arm?
- Have you ever had a severe pain across the front of your chest lasting for half an hour or more?
- In the last twelve months, have you had a sudden attack of weakness or numbness on one side of the body?
- Have you had a sudden attack of slurred speech or difficulty in finding words in the last twelve months?
- Have you had a sudden attack of vision loss or blurred vision in one or both eyes in the last twelve months?
- Do you now have, or have you ever had a heart murmur? Abnormal heart rhythm? high blood pressure (sometimes called hypertension)?
- Do you now have, or have you ever had any other heart trouble?

Health care utilisation variables

- During the two weeks ending yesterday, apart from any visit to a hospital, have you talked to a doctor on your own behalf, either in person or by telephone? Was this consultation(s) about your *(condition)*?
- During the last 2 weeks ending yesterday, did you see a practice nurse at the GP surgery on your own behalf? Was this consultation(s) about your *(condition)*?
- During the last 12 months, did you attend hospital as an out patient, day patient or casualty? Was this consultation(s) about your *(condition)*?
- And during the last year, have you been in hospital as an inpatient, overnight or longer? *(Was this stay/Were any of these stays)* because of your *(name of heart condition)*
- What treatment or advice are you currently receiving because of your high blood pressure? Blood pressure monitored by GP/other doctor/nurse
- Are you currently receiving regular check-up or monitoring because of your heart condition or stroke?
- Have you ever had an electrical recording of your heart (ECG) performed?
- Have you ever undergone any surgery or operation because of your heart condition?

Appendix 5.2. Equity estimates using bivariate probit models

		Doctor visit		Nurse visit		Inpatient visit		Outpatient visit	
		Univariate	Bivariate	Univariate	Bivariate	Univariate	Bivariate	Univariate	Bivariate
Horizontal inequity		0.0014	0.0018	-0.0129	-0.0121	0.0015	0.0027	0.0239	0.0236
Vertical inequity									
Target:	Richer 50%	0.0062	0.0041	0.0062	0.0046	-0.0005	0.0007	0.0056	0.0039
	Having degree	0.0219	0.0218	0.0137	0.0147	0.0148	0.0140	0.0282	0.0276
Total inequity									
Target:	Richer 50%	0.0076	0.0059	-0.0067	-0.0075	0.0018	0.0033	0.0295	0.0278
	Having degree	0.0233	0.0236	0.0007	0.0026	0.0163	0.0166	0.0521	0.0515
	Rho (p value)	0.4402 (0.0000)				0.7222 (0.0000)			

Appendix 5.3. Equity estimates allowing different functional forms to the CVD-related need index

		Doctor visit		Nurse visit		Inpatient visit		Outpatient visit	
		Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear
Horizontal inequity		0.0014	0.0026	-0.0129	-0.0121	0.0015	0.0023	0.0239	0.0271
Vertical inequity									
Target:	Richer 50%	0.0062	0.0038	0.0062	0.0054	-0.0005	-0.0039	0.0056	-0.0066
	Having degree	0.0219	0.0155	0.0137	0.0129	0.0148	0.0078	0.0282	0.0198
Total inequity									
Target:	Richer 50%	0.0076	0.0064	-0.0067	-0.0067	0.0018	-0.0016	0.0295	0.0205
	Having degree	0.0233	0.0181	0.0007	0.0007	0.0163	0.0101	0.0521	0.0469

		Monitor BP		Regular check-ups		ECG test		Surgery	
		Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear
Horizontal inequity		-0.0150	-0.0150	-0.0142	-0.0106	0.0498	0.0548	0.0452	0.0452
Vertical inequity									
Target:	Richer 50%	-0.0095	-0.0095	0.0047	0.0019	0.0096	-0.0001	0.0254	0.0254
	Having degree	0.0091	0.0091	0.0445	0.0335	0.0287	0.0234	0.0350	0.0350
Total inequity									
Target:	Richer 50%	-0.0245	-0.0245	-0.0095	-0.0086	0.0594	0.0547	0.0706	0.0706
	Having degree	-0.0059	-0.0059	0.0302	0.0229	0.0784	0.0782	0.0803	0.0803

Note: BP = Blood pressure; ECG = Electrical recording of the heart,

Appendix 5.4. Equity estimates using different targets

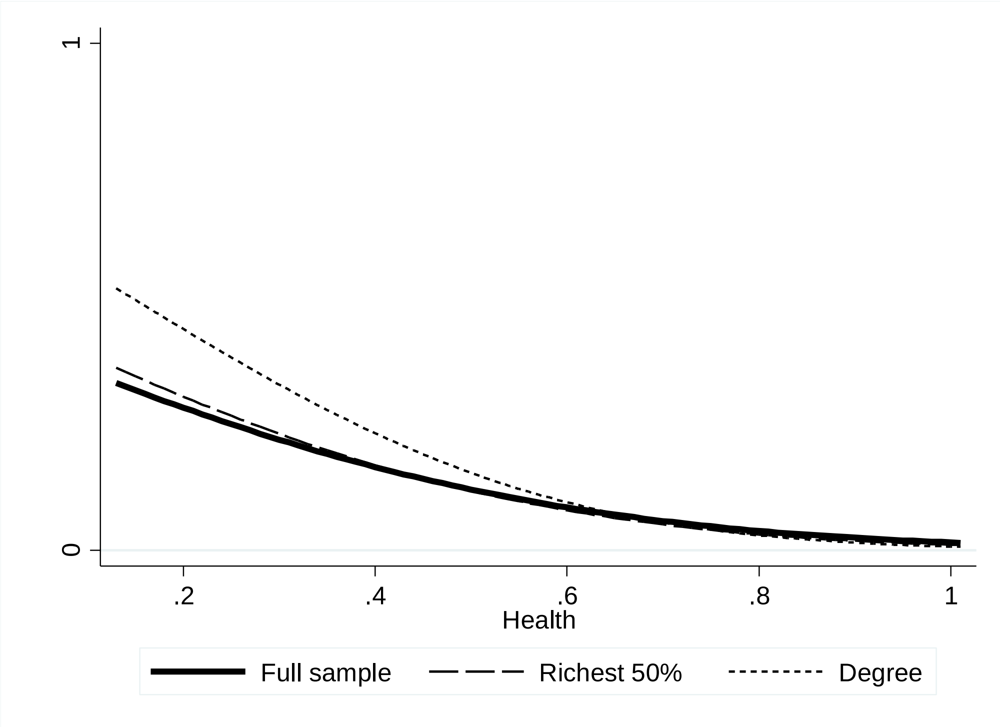
		Doctor visit		Nurse visit		Inpatient visit		Outpatient visit	
		Target1	**Target2**	**Target1**	**Target2**	**Target1**	**Target2**	**Target1**	**Target2**
Horizontal inequity		0.0014	0.0014	-0.0129	-0.0129	0.0015	0.0015	0.0239	0.0239
Vertical inequity									
Target:	Income	0.0062	0.0048	0.0062	0.0024	-0.0005	-0.0039	0.0056	-0.0008
	Education	0.0219	0.0050	0.0137	-0.0025	0.0148	0.0030	0.0282	0.0013
Total inequity									
Target:	Income	0.0076	0.0062	-0.0067	-0.0106	0.0018	-0.0024	0.0295	0.0231
	Education	0.0233	0.0064	0.0007	-0.0154	0.0163	0.0045	0.0521	0.0252

		Monitor BP		Regular check-ups		ECG test		Surgery	
		Target1	**Target2**	**Target1**	**Target2**	**Target1**	**Target2**	**Target1**	**Target2**
Horizontal inequity		-0.0150	-0.0150	-0.0142	-0.0142	0.0498	0.0498	0.0452	0.0452
Vertical inequity									
Target:	Income	-0.0095	-0.0080	0.0047	0.0112	0.0096	0.0090	0.0254	0.0266
	Education	0.0091	0.0018	0.0445	0.0152	0.0287	0.0092	0.0350	0.0182
Total inequity									
Target:	Income	-0.0245	-0.0230	-0.0095	-0.0031	0.0594	0.0588	0.0706	0.0719
	Education	-0.0059	-0.0133	0.0302	0.0010	0.0784	0.0590	0.0803	0.0635

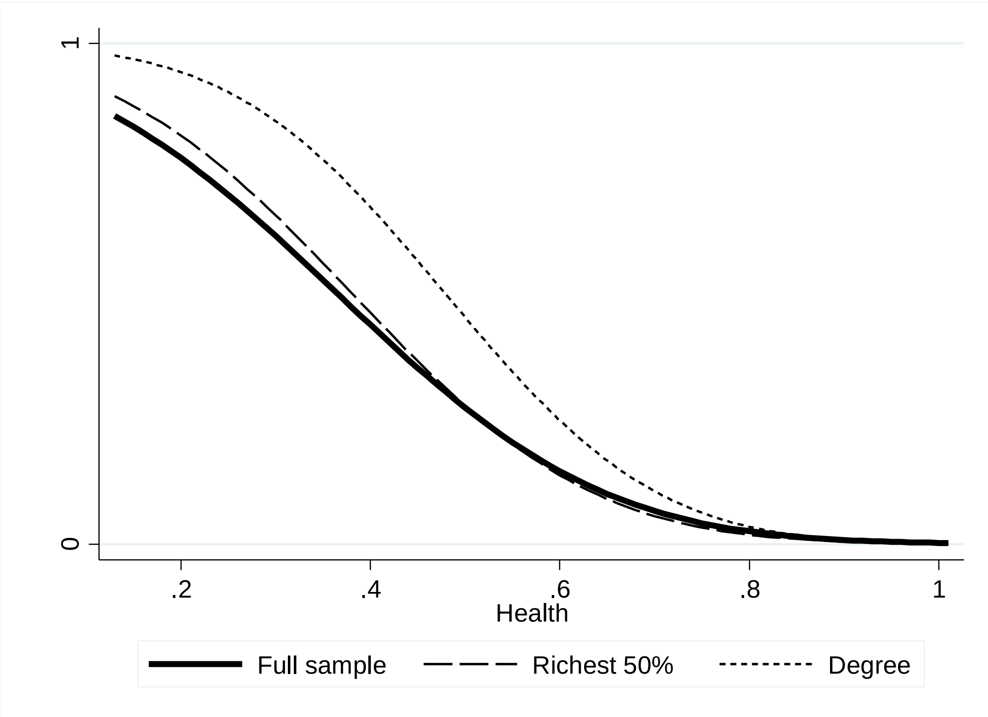
Note: Income target 1 includes the richest 50% of the population; Education target 1 includes individuals educated to the degree level; Income target 2 includes the richest 50% of the population but excludes the richest 5%; Education target 2 includes individuals with any qualification.

Appendix 5.5. Effect of health variable on health care utilisation

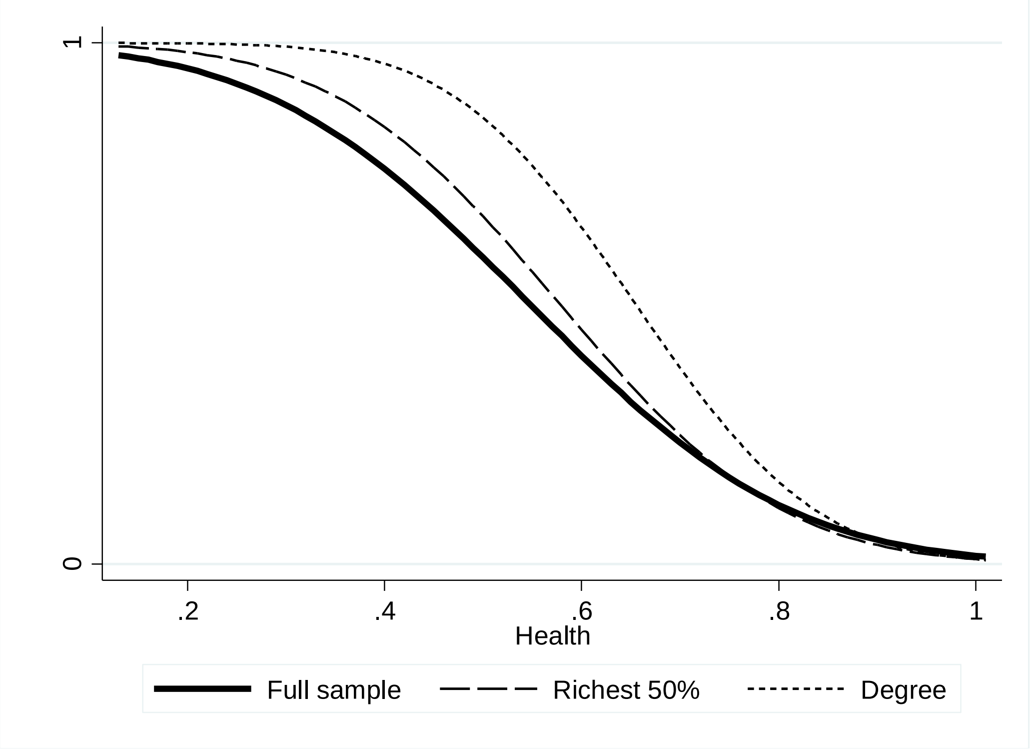
Probability of practice nurse visit



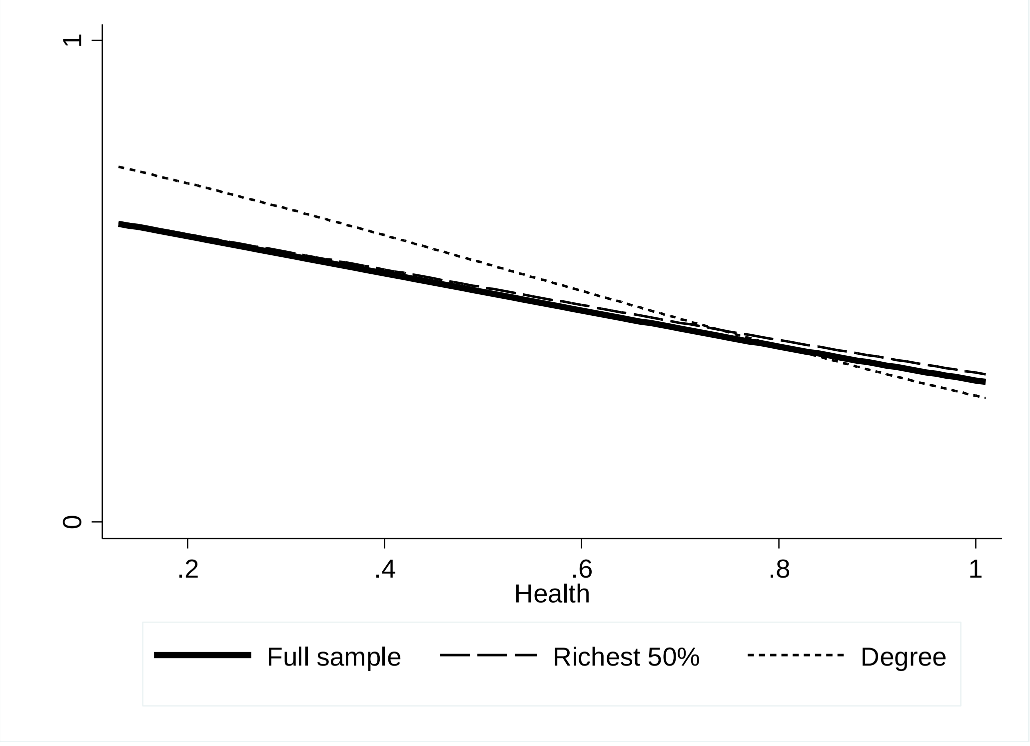
Probability of inpatient stay



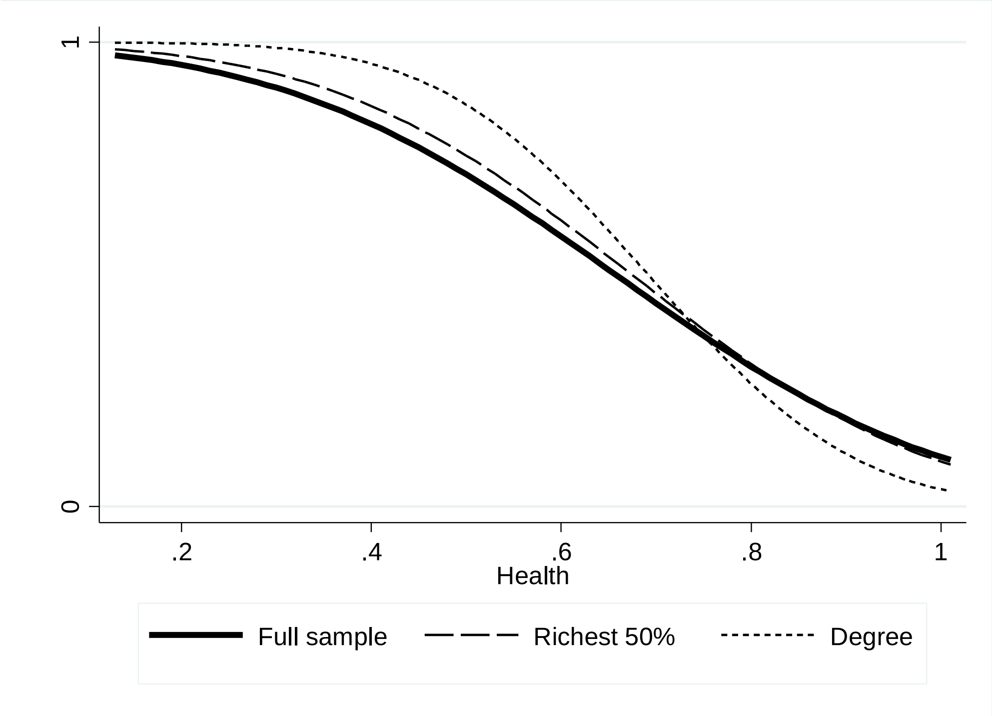
Probability of outpatient visit



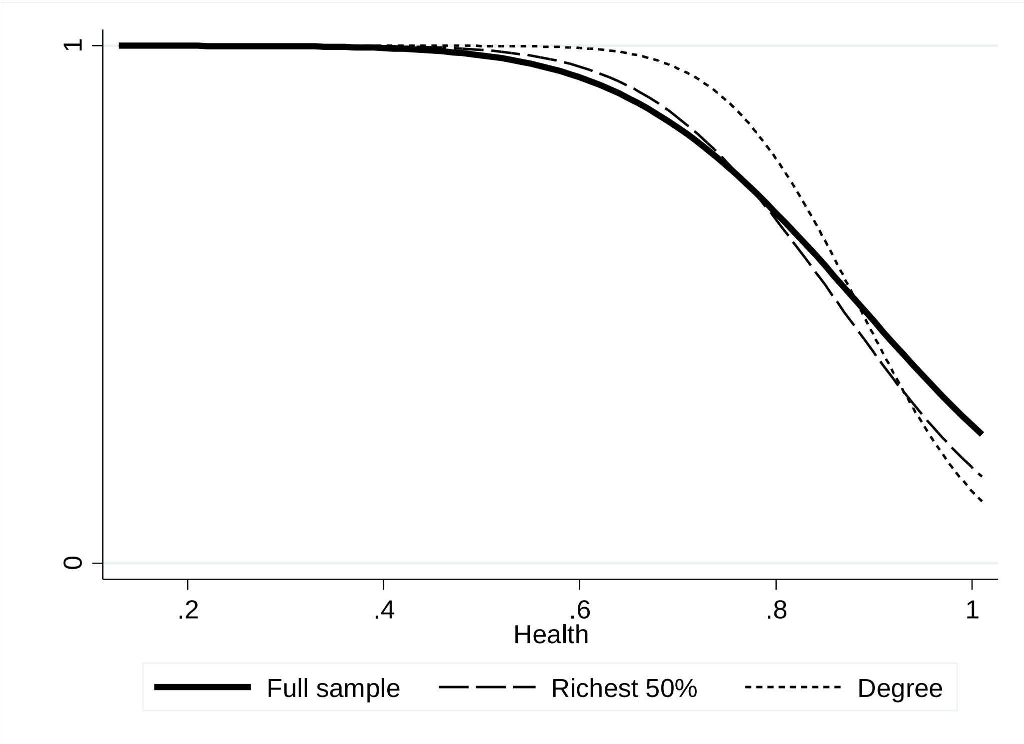
Probability of blood pressure monitoring



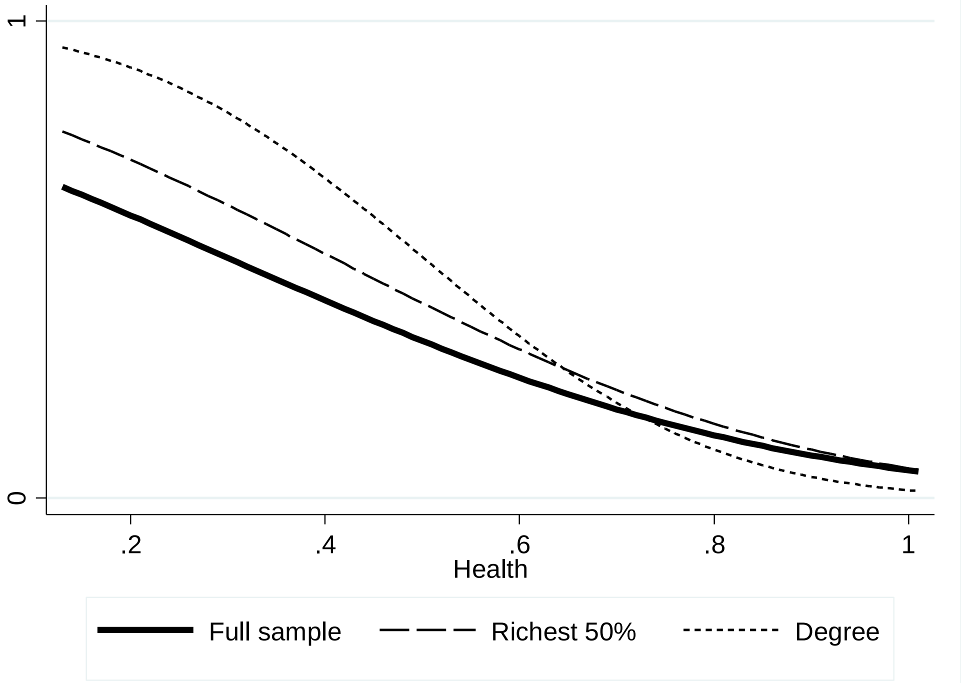
Probability of heart check-ups



Probability of ECG test



Probability of heart surgery



Appendix 5.6. Percentage of individuals across the health distribution in full sample and target groups

CVD-related health index	Full sample	Richest 50%	Degree
<0.6	2%	1%	1%
0.6-0.7	6%	4%	3%
0.7-0.8	19%	13%	10%
0.8-0.9	65%	73%	73%
>0.9	8%	9%	13%
N	10,254	5,132	1,447

Appendix 5.7. Supplementary analysis - testing for sample selection bias due to missreporting of CVD conditions

A feature of the HSE is that only individuals reporting a history of any of the CVD conditions considered in the survey were subsequently asked about their health care utilisation. Previous evidence using the same survey have found the lack of awareness or misreporting of CVD manifestations such hypertension to be a common occurrence (Johnston *et al.*, 2009). If individuals who are not aware or do not report to have CVD are different in unobservable ways which also affect their utilisation of health services, our analysis could be affected by sample selection bias. We use additional information available in the HSE to investigate this issue.

We try to identify individuals with CVD who are unaware of it using information provided in the nurse visit to identify hypertension (defined as systolic/diastolic blood pressure equal or higher than 90/140mmHg)[31] and diabetes (defined as glycated haemoglobin level equal or higher than 6.5%)[32] as well as the answers from the WHO Rose Questionnaire to detect potential angina and the questions regarding potential myocardial infarction and stroke symptoms. Using this approach we identify extra 3,398 individuals suffering from CVD according to the objective measures and reported symptom based variables who did not report to have any CVD problems. We then use sample selection models to test for this source of bias. In these models, we assume that a variable q is only observed if another latent variable S is positive,

[31] The protocol in the HSE for the measurement of blood pressure consists of taking three blood pressure readings at one-minute intervals, using an appropriately sized cuff on the right arm, with the informant in a seated position after five minutes' rest. Informants were excluded if they were pregnant. The blood pressure variables used are the means of the second and third measurements obtained from the informants in whom three readings were successfully obtained, excluding those who had eaten, drunk alcohol, exercised, or smoked in the 30 minutes before the measurement was taken.

[32] A small (non-fasting) sample of blood was taken by venipuncture from those aged 16 and over. A raised glycated haemoglobin level in the general population is indicative of undiagnosed diabetes, but the threshold for its use as a screening test is not clear (Waugh *et al*, 2007). We use the recommendation from the recent report of the International Expert Committee, 2009 which after an extensive review of both established and emerging epidemiological evidence, recommended the threshold of 6.5%.

$$q^* = \beta\ X + \mu_1$$
$$S^* = \gamma\ Z_i + \mu_2 \qquad \text{(A1)}$$

where q^* is an unobserved latent variable such that $q^* \geq 0$ if $q = 1$ and $q^* < 0$ if $q = 0$, and S^* is defined similarly. *S* =1 if we observe *q*, and zero otherwise. In our study, *q* represents the probability of using CVD-related health care services, once the individual report having CVD, and *S* represents the probability that the individual is aware and report having CVD (i.e., the dependent variable =1 if the individual report having any CVD condition and =0 if the individual is found to have CVD but does not report any CVD condition). *X* and *Z* are vectors of regressors and the error terms μ_1 and μ_2 are jointly normally distributed, independently of *X* and *Z*, with zero expectations (Wooldridge, 2003).

Identification for the sample selection model relies on finding some explanatory variables that enter the first-stage equation (i.e. the probability of reporting CVD) but do not enter the second stage regression (i.e. health care utilisation equation). In other words, *X* is a subset of *Z*, and Z includes additional variables that act as instruments. In our case some elements of *X* were perfectly correlated with the selection equation dependent variable (i.e. doctor diagnosed and reported CVD condition indicators that formed the CVD-health index predict perfectly the probability of reporting CVD), and were thus excluded from this model. Variables that were not significant in predicting the need index for CVD-related health care use, such as family history of CVD and some of the objective measures of health collected in the nurse visit, were used as instruments for the sample selection model.

The nonselection hazard (also known as the inverse Mills ratio) is then computed from the probit model of the probability of reporting CVD and added as an extra variable in the second stage regression of the outcome *q* on the set of explanatory variables. Thus, the model for the probability of using health care is specified as,

$$q^* = \beta\ X + \rho\lambda + \mu$$
$$\lambda = \varphi(\gamma\ Z) / \Phi(\gamma\ Z) \qquad \text{(A2)}$$

where Φ(.) is the cumulative distribution function of the standard normal distribution and φ(.) is the corresponding probability density function. This model is the binary model version of the sample selection model developed by Heckman, 1979. We test for sample selection by looking at the significance of the estimated selection coefficient λ included in the second equation, as well as by testing whether the coefficients are statistically significantly different with and without including the selection coefficient.

Appendix 5.8 shows the results for the first-stage equation of the probability of reporting CVD and the significance of the selection terms as well as the Hausman test results. We find that the probability of reporting CVD, among those who are considered to have CVD, depends, among other things, on the age, gender, obesity and smoking status of the individual. Interestingly, obesity increases the chances of reporting CVD while smoking status is negatively correlated with the awareness or reporting of a CVD condition. None of the socioeconomic indicators were found to influence the probability of reporting CVD; but there is some area variation effect. The presence of some of the symptom-based indicators reduces the probability of reporting CVD. This is not surprising given the specification of the model, as individuals who report any of these symptoms but did not report CVD are included as zero values in the dependent variable, and as a result the model predict that they are less likely to report CVD. With respect to the variables used as exclusion criteria in the second stage-equation, we find that family history significantly increases the probability of reporting CVD and some of the objective measures, such as the presence of hypertension as measured in the nurse visit, are significantly and negatively correlated with reporting CVD. The rationale for this negative coefficient is similar to the argument for the symptom-based measures. We find no evidence of sample selection bias (see Appendix 5.8). The selection coefficient is only significant in the model of outpatient visit, but the Hausman test reject that the coefficients are statistically significantly different.

Note however, that these sample selection models were run on a smaller sample than that used in the analyses reported in our study. The reason is that only about half of the sample had valid measures of haemoglobin levels and a similar number had valid blood pressure and cholesterol level measures, which are variables used to identify individual unaware of their CVD problems and/or used as instrument in the selection model. This may have an impact on the representativeness of this sample as those willing and able to take part in the nurse visit and provide valid values of the collected measures may be different to those not doing so. Therefore, the results based on this subsample need to be read with caution.

Appendix 5.8. Results for supplementary analyses of testing for sample selection bias

First stage equation for the probability of reporting CVD				
Variables	**Mean**	**SD**	**Coeff**	**z value**
Age/100	0.054	0.166	1.181	4.93
Age2/10000	0.031	0.039	-0.214	-0.24
Age3/1000000	0.005	0.016	0.753	0.24
Female	0.517	0.500	0.319	7.68
Symptom angina grade 1	0.022	0.146	-0.782	-5.71
Symptom angina grade 2	0.009	0.094	-0.377	-1.47
Possible myocardial infarction	0.105	0.307	-0.748	-10.56
Symptom weakness	0.059	0.236	-0.366	-3.54
Symptom slurred speech	0.035	0.183	0.045	0.33
Symptom vision lost	0.100	0.300	-0.716	-9.82
Smoker	0.184	0.388	-0.155	-2.93
Obesity	0.277	0.447	0.121	2.67
Family history of CVD	0.118	0.322	0.208	3.29
Low HDL cholesterol - nurse visit	0.093	0.290	0.062	0.86
High LDL cholesterol - nurse visit	0.765	0.424	-0.069	-1.33
Hypertension - nurse visit	0.437	0.496	-1.064	-23.06
Diabetes - nurse visit	0.051	0.219	0.084	0.78
Log income	9.946	0.928	-0.017	-0.64
Educational degree	0.179	0.383	0.036	0.64
Ethnic group white	0.934	0.248	0.132	1.39
Married	0.597	0.491	-0.051	-1.15
North East	0.054	0.225	-0.215	-1.90
North West	0.139	0.346	-0.289	-3.13
Yorkshire	0.110	0.313	-0.148	-1.59
East Midlands	0.094	0.292	-0.112	-1.15
West Midlands	0.113	0.317	-0.138	-1.42
East of England	0.101	0.301	-0.053	-0.55
South East	0.180	0.384	-0.154	-1.73
South West	0.114	0.318	-0.173	-1.80
Year 2006	0.456	0.498	-0.045	-1.08
N		5,393		

Second stage equation models (main results)				
	Test of selection term significant in 2nd stage		Hausman test of coefficients significantly different	
	Chi-square	p-value	Chi-square	p-value
Doctor visit	0.01	0.943	0.02	1.000
Nurse visit	0.17	0.680	0.66	1.000
Inpatient visit	2.35	0.125	9.88	0.970
Outpatient visit	6.50	0.011	14.39	0.810
Monitor BP	2.21	0.137	4.39	1.000
Regular check-ups	0.70	0.401	1.29	0.999
ECG test	0.09	0.758	0.17	1.000
Surgery	0.10	0.753	0.26	1.000

Appendices to Chapter 6

Appendix 6.1. Gini indices and concentration indices of needs with respect to income

Sample	Index	Ratio
All CVD		
Gini index of needs	0.0456	
CI of need with respect to income	0.0124	0.271
High blood pressure sample		
Gini index of needs	0.0460	
CI of need with respect to income	0.0128	0.288
Angina/heart attack/stroke/irregular heart rhythm/'other' heart problem sample		
Gini index of needs	0.0607	
CI of need with respect to income	0.0173	0.279

Appendices to Chapter 7

Appendix 7.1. Estimates of inequity in expenditure on cancer using observed number of cancer deaths instead of SMR from cancer

	SES-related		Need-related	
	CI	**CI/SE**	**CI**	**CI/SE**
Actual (CI_T)	-0.2252	-18.26	-0.3433	-31.03
Horizontal inequity				
Conventional	-0.0345	-1.32	0.0184	0.54
Conservative	-0.0187	-0.95	0.0219	0.83
Vertical inequity	0.0127	0.29	0.0795	1.28
Total inequity				
Conventional	-0.0233	-0.36	0.0976	1.20
Conservative	-0.0060	-0.13	0.1014	1.53

Note: SES = Socioeconomic Status; CI = Concentration Index; SE = Standard Error.

Standard errors are derived using bootstrapping techniques.

Appendix 7.2. World Class Commissioning framework assurance system

The WCC programme is designed to improve PCT commissioning and to lead to "the delivery of better health and wellbeing" in the NHS (Department of Health, 2008c). Underpinning the programme is an "assurance system" that assesses PCTs' performance through a national appraisal system managed by SHAs and that is designed to enable reliable comparison of performance across all PCTs. In this system, PCTs are assessed in terms of their outcomes, competencies and governance, and these are scored using a combination of approaches including self-assessment, self-certification, feedback from partners, evidence gathering and review of data. There are 11 competencies in the assurance system. These require that PCT commissioners are: [33]

1. Recognised as the local leader of the NHS.
2. Work collaboratively with community partners to commission services that optimise health gains and reductions in health inequalities.
3. Proactively seek and build continuous and meaningful engagement with the public and patients, to shape services and improve health.
4. Lead continuous and meaningful engagement with clinicians to inform strategy, and drive quality, service design and resource utilization.
5. Manage knowledge and undertake robust and regular needs assessments that establish a full understanding of current and future local health needs and requirements.
6. Prioritise investment according to local needs, service requirements and the values of the NHS.
7. Effectively stimulate the market to meet demand and secure required clinical, and health and well-being outcomes.
8. Promote and specify continuous improvements in quality and outcomes through clinical and provider innovation and configuration.
9. Secure procurement skills that ensure robust and viable contracts.
10. Effectively manage systems and work in partnership with providers to ensure contract compliance and continuous improvements in quality and outcomes.
11. Make sound financial investments to ensure sustainable development and value for money.

[33] Department of Health Commissioning Team. *World Class Commissioning: Competencies*. London: Department of Health, 2007.

Of these 11 competencies, the first ten are assessed within the competencies element of commissioning assurance. The eleventh competency - making sound financial investments - is assessed within the governance element. Each of the remaining ten competencies is assessed based on three indicators. Each indicator is assessed against a four point scale (levels one to four, where level one is the lowest level and level four is "world class"). We are interested in good performance by PCTs with respect to allocating resources internally according to the needs of the populations they serve, and to reducing health inequalities. Competencies 2, 5 and 6 focus explicitly on these issues. The indicators for these competencies are listed below,

- Competency 2 (Work with community partners):
    - creation of Local Area Agreement based on joint needs;
    - ability to conduct constructive partnerships; and,
    - reputation as an active and effective partner.
- Competency 5 (Manage knowledge and assess needs):
    - analytical skills and insight;
    - understanding of health needs trends; and,
    - use of health benchmarks.
- Competency 6 (Prioritise investment):
    - predictive modelling skills and insights;
    - prioritisation of investment to improve population's health; and,
    - incorporation of priorities into strategic investment plan.

Appendix 7.3. Vertical and horizontal inequity estimates using ranking variable based on cases per capita and job seekers' claimant per capita

	SES-related		Need-related	
	CI	CI/SE	CI	CI/SE
Horizontal inequity				
Conventional	-0.0493	-1.57	0.0209	0.62
Vertical inequity	-0.0656	-1.29	0.0659	1.25
Total inequity				
Conventional	-0.1150	-1.60	0.0868	1.17

Note: SES = Socioeconomic Status; CI = Concentration Index; SE = Standard Error.

Appendix 7.4. Vertical and total inequity estimates using separate target indicators

Target group	Vertical inequity		Total inequity	
	SES-related	Need-related	SES-related	Need-related
Base case	*0.0141*	0.0802	-0.0202	*0.0973*
SMRcanc75	0.0047	0.0105	-0.0314	0.0301
Survival5year	0.0219	0.0836*	-0.0152	0.1028
Emerlung	0.0399	0.0729	0.0038	0.0922
Reftww	-0.0025	0.0297	-0.0392	0.0491
Diagtww	-0.0330	0.0327	-0.0709*	0.0518
Compliant62	-0.0103	-0.0123	**-0.0463**	0.0074
Screcervical	-0.0103	0.0154	-0.0469	0.0348
Screbreast	-0.0124	0.0110	-0.0490	0.0304
Competency2	0.0004	0.0054	-0.0355	0.0250
Competency5	0.0052	0.0280	-0.0311	0.0474
Competency6	0.0386	0.0352	0.0031	0.0550
Needindex	0.0046	0.0048	-0.0313	0.0244
Caseseffect	0.0277	0.1003	-0.0097	0.1194

Note: See Appendix 7.1 for variable definitions. Indices in bold are significant at 5% significance level, indices with star are significant at 10% significance level. Bootstrapping techniques are used to compute standard errors around equity estimates.

Appendix 7.5. Estimates of inequity in expenditure on cancer including supply and regional indicators among the need variables

	SES-related		Need-related	
	CI	CI/SE	CI	CI/SE
Actual (CI_T)	-0.2252	-18.26	-0.3433	-31.03
Horizontal inequity				
Conventional	-0.0351	-1.38	0.0094	0.29
Conservative	0.0199	0.78	0.0199	0.79
Vertical inequity	0.0104	0.26	0.0559	1.26
Total inequity				
Conventional	-0.0260	-0.47	0.0650	1.09
Conservative	0.0758	1.28	0.0758	1.43

Note: SES = Socioeconomic Status; CI = Concentration Index; SE = Standard Error.

Standard errors are derived using bootstrapping techniques.

Appendix 7.6. Estimates of inequity in expenditure on cancer (comparing short-run and long-run estimates)

	SES-related		Need-related	
	LR	**ASR**	**LR**	**ASR**
Actual (CI_T)	-0.2252	-0.2203	-0.3433	-0.3406
Horizontal inequity				
Conventional	-0.0345	-0.0379	0.0171	0.0192
Conservative	-0.0187	-0.0288	0.0199	0.0209
Vertical inequity	0.0144	0.0145	0.0802	0.0804
Total inequity				
Conventional	-0.0202	-0.0234	0.0973	0.0996
Conservative	-0.0043	-0.0143	0.1002	0.1013

Note: SES = Socioeconomic Status; CI = Concentration Index; LR = long-run CI; ASR = average short-run CI

Appendix 7.7. Estimates of inequity in expenditure on cancer (standard errors based on the standard errors around the point estimates of the CI of the standardised variables)

	SES-related		Need-related	
	CI	**CI/SE**	**CI**	**CI/SE**
Actual (CI_T)	-0.2252	-18.26	-0.3433	-31.03
Horizontal inequity				
Conventional	-0.0345	-7.55	0.0171	3.99
Vertical inequity	0.0144	3.52	0.0802	34.99
Total inequity				
Conventional	-0.0202	-2.86	0.0973	18.35

Note: SES = Socioeconomic Status; CI = Concentration Index; SE = Standard Error.