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Inequity and inequality in the use of health care in England: an empirical investigation

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Abstract

We investigate inequality and inequity in the use of GPs, outpatient visits, day cases and inpatient stays with a unique linked data set which combines rich recent information on the subjective and objective health of individuals and their socio-economic circumstances with information on local supply conditions. After controlling for need variables such as age, sex, health and for the supply of health care, we find that utilisation is linked to income, ethnicity, economic status and education. Low-income individuals and ethnic minorities have lower use of secondary care despite having higher use of primary care.

We also calculate indices measuring overall inequality of use and measuring income related inequality of use and determine the separate contributions of need, income and other non-need factors to these indices. Need variables (age, gender, health) make the largest contribution to overall inequality. They also make the largest pro-poor contribution to income related inequality in use because they have a large positive effect on use and are negatively correlated with income. Income itself makes a relatively small direct contribution to both income related inequality and to overall inequality in use. The contributions of economic status and education to overall inequality are larger than that of income. The contribution of ethnicity to income related inequality is larger than the direct contribution of income.

Key words: Inequity. Inequality. Concentration index. Ethnicity. GP consultations. Inpatient stays. Health measures. Utilisation.

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1 Introduction

The pursuit of equity is a key objective of many healthcare systems and has received special emphasis in the National Health Service (NHS) in the UK. In this paper we test for the existence of horizontal inequity in the use of the NHS in England. We also attempt to measure the extent of both inequality and inequity and to estimate the contribution of different factors to them.

A wide range of factors influences individual use of health services. To test for and to measure the extent of inequity requires value judgements to distinguish between need variables which ought to affect use and non-need variables which ought not. There is horizontal equity when individuals with the same needs consume the same amount of health care. If use varies with non-need variables there is horizontal inequity. There is vertical equity when individuals with different levels of need consume appropriately different amounts of health care. The concept of need is problematic (Culyer, 1995) and we adopt a pragmatic approach, presenting our results in such a way that readers with different views of what constitutes need can readily test for and measure the extent of horizontal inequity based on their judgements of which variables are need variables.

Despite the importance of equity in health care use, there is relatively little systematic evidence for the UK. Goddard and Smith (2001) conducted a comprehensive review of research over the period 1990-1997. They concluded that, while there appear to be inequities in utilisation for some types of care, the evidence is often methodologically inadequate. In particular they point to the difficulties associated with definitions and measurement of need.

The most comprehensive analyses of health care inequity in the UK based on individual level data have come from the pioneering work of the ECuity project (http://www.eur.nl/bmg/ecuity/). Van Doorslaer, Wagstaff, van der Burg et al (2000) used the UK General Household Survey for 1989 to consider the extent to which GP visits, outpatient visits and inpatient stays vary with income. The results confirm Goddard and Smith's (2001) emphasis on the importance of the need adjustment. For example, with the crudest need variables the distribution of GP visits was pro-poor, but with more detailed need variables GP visits were unrelated to income.

They also found that income had a positive but not statistically significant association with outpatient visits and a significant positive association with inpatient stays. More recent results from the ECuity II project based on data from British Household Panel Survey from the mid 1990s find pro-poor inequity for GP consultations and strongly pro-rich inequity for specialist visits (van Doorslaer, Koolman and Puffer, 2002; van Doorslaer, Koolman and Jones, 2002).

Our data set enables us to make a number of contributions. First the data is more recent than in earlier studies, covering the period 1998 to 2000. The election of the Labour government in May 1997 led to an increased policy concern with equity issues (Department of Health, 2000a, 2000b, 2002a, 2003a). There have been a number of developments with possible implications for equity in England: the unification and devolution of budgets to 304 Primary Care Trusts instead of 95 Health Authorities (Department of Health, 1997; Pollock, 2001); the abolition of budgets for fundholding practices; greater autonomy for hospitals (McGauran, 2002; Dixon, 2003); greater freedom for patients to choose a hospital (Department of Health, 2003b); new pricing rules to encourage competition amongst hospitals (Department of Health, 2002b); the introduction of a new contract for GPs with greater emphasis on quality of care (Department of Health, 2003c); new budget allocation formulas based on new measures of need covering the bulk of NHS funds (Department of Health, 2003c; Sutton, Gravelle, Morris et al, 2002); and the introduction of National Service Frameworks intended to reduce variations in treatment patterns (Department of Health, 2003d). Our results provide a baseline to assess the equity effects of these policies.

Second, previous studies have shown that different measures of need can lead to difference conclusions about the existence and extent of inequity. Our data set has a very rich set of morbidity measures including both self reported and objective measures, and hence we are able to better allow for need when measuring variations due to non-need factors such as income or ethnicity. Third, and uniquely, we have been able to link the individual level data with small area (ward level) data on supply conditions. Previous studies either ignore the effect of supply conditions on use or have to use much more aggregated (local or health authority) measures.

We adopt the approach taken by Newbold, Eyles and Birch (1995) and Abasolo, Manning and Jones (2001) and consider multiple need and non-need determinants of health care use.

The socio-economic variables include income, social class, economic activity, and educational attainment. We also consider the effect of ethnicity which has been shown previously to influence the use of various types of health care services in Britain (Smaje and Le Grand, 1997), and which is an area of policy concern in England (Department of Health, 2000b).

Our basic approach is to model the determinants of health care use by multiple regression of use on a large set of morbidity, demographic, socio-economic, and supply variables. The *test* for horizontal inequity is to examine the significance and sign of variables commonly felt to be non-need variables. The non-need variables we focus on include income, education, social class and ethnicity. We measure the *extent* of health care inequality and inequity using the health care concentration index (Wagstaff, van Doorslaer and Paci, 1991; Wagstaff and van Doorslaer, 2002) which is analogous to the Gini coefficient often used to measure inequality in the distribution of income. We use the concentration indices to examine both income-related inequality and total inequality in utilisation. We decompose the concentration index to examine the contribution of need, supply and non-need factors to health care inequalities.

The data are described in the next section. The analytical methods are discussed in section 3. The results of the regression models are presented in section 4, and those on the extent of inequality and horizontal inequity are presented in section 5. Section 6 concludes.

2 Data and variables

2.1 Data sources

The analysis is based on pooled data from three rounds (1998, 1999, 2000) of the Health Survey for England (HSE). The HSE is a nationally representative survey of individuals aged two years and over living in England.[1] A new sample is drawn each year and respondents are interviewed on a range of core topics including demographic and socio-economic indicators; general health and psychosocial indicators; and use of health services. Additionally, there is a follow up visit at which a nurse takes various physiological measurements (e.g. height, weight, waist-hip ratio, cholesterol and blood pressure).

The sample size combining all observations across 1998-2000 is 50,977. The core nationally representative sample of respondents was supplemented with a boost sample from ethnic minorities in 1999 and from older people in 2000. We include the boost samples and do not need to weight observations since we include the boost factors (ethnicity, age) in the regression models. The resulting increase in sample size provides more precise estimates of the coefficients.

Each individual in the sample was matched, via their post-code, to one of the 8,414 local authority wards in England. A range of ward-level variables were then attributed to the individuals. They included the supply variables used in the recent review of allocation formulae for hospital services, community health services and general practice prescribing in the NHS in England (Sutton, Gravelle and Morris et al., 2002; Gravelle, Sutton and Morris et al, forthcoming).

2.2 Health care utilisation

From 1998 onwards individuals participating in the HSE have been asked about their use of four types of health service. For outpatient visits, day case treatments, and inpatient stays, use is measured as binary variable since individuals are asked only whether or not they had that type of use in the previous 12 months. For GP consultations, respondents are asked if they had a GP consultation in the last 2 weeks and, if so, the number of consultations. Very few respondents had more than one GP consultation in this short period: 84% had no visits, 13% had one visit, and 3% had more than one visit. We therefore also measure GP use as whether the respondent had a GP visit or not.

2.3 Health variables

We make use of the wide range of health indicators available in the HSE. These include: self-reported general health; acute ill health; specific longstanding illnesses; and GHQ-12 scores. Self-reported general health is assessed on a five-point scale from "very good" to "very bad". [2] Respondents are also questioned about their health in the last two weeks (*acute* ill-health). [3] They are also asked whether they have longstanding illness and its type. [4] We also include a dummy variable indicating whether at least one of these illnesses is limiting. We measure the extent of co-morbidity by the number of longstanding illnesses.

Nurse administered physiological measures of health status include: systolic blood pressure (units of measurement = mm Hg); Body Mass Index (kg/m^2); height (m); weight (kg); total cholesterol (mmol/l); HDL cholesterol (mmol/l); haemoglobin (g/dl); fibrinogen (g/l); ferritin (ng/ml); and waist:hip ratio. To capture potential non-linearities in the relationship between the physiological measures and utilisation we include quadratic terms for all of the variables except Body Mass Index (BMI). We measure BMI grouped in six commonly-used bands: underweight (<20); healthy (20-25); overweight (25-30); obese (30-35); morbidly obese (35-40); and dangerously obese (>40).

In addition to the individual-level health variables we include two area-based indicators. The first, the Standardised Mortality Ratio for the ward population aged less than 75 years (SMR<75), provides an estimate of the individual respondent's mortality risk. The second, the Standardised Illness Ratio for the ward population aged less than 75 years (SIR<75), is designed to reflect broader contextual effects.

In presenting the results, the rich set of health variables are grouped into three categories:

Crude self-reported health measures: self-assessed general health; limiting longstanding illness; acute ill health.

Detailed self-reported health measures: type and number of longstanding illnesses; GHQ-12 scores.

Objective health measures: physiological measures of health status; ward-level mortality and morbidity risk.

The health variables in the first category are included regularly in most of the general household surveys that have been used previously for measuring equity in the UK (e.g. the British Household Panel Study and the General Household Survey). The detailed health measures included in the second category tend to be asked only in health surveys such as the HSE or in specific waves of general household surveys. The objective health measures are not found in general household surveys and have not been used in previous analyses of equity in England.

2.4 Income

Our income variable is derived from the income of the whole household before deductions for income tax and national insurance. There are 31 income bands of different widths with an open-ended top band. To quantify the effect of income on health service utilisation we require a continuous income variable. We estimated the median level of household income within each band (including the top open-ended band) as our measure of household income for all individuals within each band. We compared the frequency of observations within each income band with the numbers that would be generated by the log normal distribution, which is often used to characterise income distributions (Cowell, 1995; Lambert, 2001). The mean and standard deviation parameters of the log normal distribution were determined by minimising the sum of squared differences between actual and generated numbers in each band. The median income in each band was then computed as the value at half the cumulative density within the band.

The resultant estimate of household income for each respondent was then equivalised to allow for differences in household size and composition using the McClements scale (McClements, 1977). As in van Doorslaer, Wagstaff and van der Burg et al (2000) we used the natural logarithm of the equivalised income as the income measure, after comparison with results from power functions of income.

2.5 Socio-economic variables and ethnicity

The HSE includes Registrar General's Social Class of the head of household, and we treat each group separately: I professional; II managerial technical; IIIN skilled non-manual; IIIM skilled manual; IV semi-skilled manual; V unskilled manual; and other. Respondents are also asked questions on the highest educational qualification that they have attained and we consider seven groups: degree or equivalent; higher education qualification less than a degree; A level or equivalent; GCSE or O level or equivalent; CSE or equivalent; other qualifications; and no formal educational qualifications.

The HSE also provides information on economic activity in nine categories: in paid employment or self-employed; waiting to take up a job already obtained; looking for work;

intending to look for work but prevented by temporary sickness or injury; going to school or college full time; permanently unable to work because of long term sickness or injury; retired; looking after the home or the family; and doing something else.

The effects of ethnicity are captured with nine binary indicators: White; Black Caribbean; Black African; other Black ethnic group; Indian; Pakistani; Bangladeshi; Chinese; and other non-White ethnic group.

2.6 Supply variables

After experimenting with a variety of ward-level supply variables we selected four: the Index of Multiple Deprivation access domain score;[5] average proportion of outpatients seen within 26 weeks at providers used; average GPs per 1,000 patients at the practices with which the ward residents are registered, and average distance to acute providers used. These are used in the GP consultation, outpatient visit, day case treatment and inpatient stay models, respectively. Additionally we include Health Authority (HA) effects in the utilisation models to control for unobserved supply factors (see Sutton, Gravelle and Morris et al. (2002) and Gravelle, Sutton and Morris et al (forthcoming) for a discussion of the rationale). Since wards may cross HA boundaries we measure HA effects using a vector of 94 variables representing the proportion of each ward's population resident within each HA.

3 Analysis

Testing for and measuring horizontal inequity both require a positive model of the determinants of health service use and a set of value and factual judgements. Different value judgements may affect conclusions about the existence of inequity but the same positive model can be used to test for inequity and to measure the extent of inequality and inequity whatever the set of value judgements adopted.

3.1 Testing for horizontal inequity

To illustrate, suppose that the best fitted model of individual health service use is linear in the explanatory variables:

$$U = b_0 + b_1 morbidity + b_2 age + b_3 income + b_4 ethnicity + b_5 supply + residual \qquad (1)$$

where supply might be measured by the number of hospital beds in the local area. Need variables are those variables which one believes ought to affect use. There is horizontal inequity if, holding need variables constant, use varies with non-need variables which ought not to affect it. Suppose that we agree that neither income nor ethnicity ought to affect use. Then there is horizontal inequity if either $b_3 \neq 0$ or $b_4 \neq 0$.

Although the value judgements that morbidity should affect use and that income and ethnicity should not may be uncontroversial, there is likely to be more disagreement about other variables such as age and supply. Williams (1997) has suggested that entitlement to health care should decline with age since capacity to benefit declines and older individuals have achieved more of their "fair innings" of life expectancy. On this view b_2 should be negative. Others might argue that if morbidity measures capture all the potential for an individual to benefit from health care then age ought to have no effect ($b_2 = 0$). But it can also be argued that morbidity measures will never capture all of the capacity to benefit from care and that the unobserved component is positively correlated with age. Or providing more care to older individuals, even if it is less effective, can be seen as a sign of social solidarity or as a means of compensating the elderly for other disadvantages (such as lower incomes). These latter arguments imply that use should increase with age: $b_2 > 0$. Thus whether a finding that use increases with age is evidence of horizontal inequity depends on one's underlying value judgements.

The supply variable differs from the other variables in the utilisation equation in that inequality and inequity in access are of policy interest in their own right. Indeed, some commentators have argued that policy should be directed at variations in access rather than in use (Mooney, Hall and Donaldson et al, 1991). It would be possible to test for horizontal inequity in access by regressing supply on morbidity, age, income, ethnicity and other variables. Non-zero coefficients on the non-need variables such as income or ethnicity would then be evidence of horizontal inequity in access. However, our focus in this paper is on inequity in utilisation, not inequity in supply, and so we must consider whether the coefficient on the supply variable in the utilisation equation provides evidence about horizontal inequity in utilisation.

Typically individuals in areas with greater supply have greater utilisation ($b_5 > 0$). As with age, the implications of the sign of the coefficient on supply for horizontal equity depends on both value judgements and judgements of fact. For example, one may believe that the reason that individuals have greater use if they live in areas with greater supply is that they have lower access costs in the form of shorter distances to travel or shorter waiting times. If one makes the value judgement that use of health services should not be affected by access costs, then $b_5 > 0$ is evidence of horizontal inequity. This judgement would imply that two patients with the same morbidity should have the same number of GP visits irrespective of whether they live very close to a general practice or whether they live in a remote area and would incur heavy access costs. If instead one makes the value judgement that use ought to be greater when access costs are lower, because the individual's net benefit from use is thereby greater, then supply ought to affect use, and $b_5 > 0$ is not an indication of horizontal inequity.

As a second example, one may believe that access costs have no effect on use and that $b_5 > 0$ because a variable which has a positive effect on use and which is positively correlated with supply has been omitted from the health equation (1). Hence the coefficient on the supply variable is picking up the effect of the omitted variable. $b_5 > 0$ is not evidence for horizontal inequity if one makes the value judgement that the omitted variable is a need variable (perhaps some aspect of morbidity not reflected in the morbidity measures already included in the utilisation equation). On the other hand if one believes that the omitted variable is not a need variable then $b_5 > 0$ is evidence of horizontal inequity.

There is some debate in the resource allocation literature about whether supply is correlated with omitted need variables (Carr-Hill et al, 1994; Gravelle et al, 2003). If it is, the positive coefficient on supply in the utilisation model is not evidence for horizontal inequity since supply is acting as a proxy for unobserved need variables in addition to any direct effect of supply on use via access costs. Given the rich set of health measures in our data set, we incline to the view that little of our estimated positive effect of supply on use can be attributed to omitted need. But, even if supply is not a proxy need variable, it may still be a need variable in its own right if one believes that access costs should be taken into account in determining use. Hence the interpretation of the coefficient on the supply variable depends on judgements of value and of fact.

Irrespective of their equity interpretation, the effects of supply factors on use are important for testing for and measuring horizontal inequity in use: measures of access and supply should be included in estimated utilisation models. If they are omitted their effect on use will picked up by the coefficients on the other variables in the model with which they are correlated. Omitting supply factors may vitiate the tests of horizontal equity based on the coefficients of the remaining variables.

3.2 Testing for vertical inequity in utilisation

There is vertical equity when utilisation varies appropriately with the factors which ought to affect use. In terms of the model we require a judgement about what the size of the coefficient on morbidity should be, not just its sign. This implies stronger value judgements and more information about the effect on use. Unsurprisingly there have been few attempts to test for and measure vertical inequity (Sutton (2002) is a rare example) and we restrict our attention to horizontal inequity.

3.3 Measuring horizontal inequality and inequity with respect to income

Wagstaff, van Doorslaer and Paci (1991) reviewed measures of socio-economic inequalities in health and suggested that the most appropriate was the *concentration index*. It is analogous to the Gini coefficient, commonly used as a measure of income inequality (Cowell, 1995; Lambert, 2001). The concentration index is derived by ranking the population by a measure of socio-economic circumstances which it is believed ought not to affect utilisation and comparing the share of total utilisation accruing to people in different ranks with their share of the population. Typically researchers focus on the inequality arising from the effect of income on use. The concentration index of use against income is derived from the concentration curve (analogous to the Lorenz curve) which graphs the cumulative proportion of use against the cumulative proportion of the population ranked by income. If there is no income related inequality in use the poor will have, on average, the same use as the rich and the poorest k% of the population will have k% of total population use. The concentration curve will then coincide with the 45^o line. If poor people have less use than the rich the poorest k% will have less than k% of total use and the concentration curve will lie below the 45^o line. The concentration index is proportional to the area between the 45^o line and the concentration curve and is positive if the concentration curve lies below the 45° line (pro rich inequality) and negative if it lies above it (pro-poor inequality).

If the estimated model of the determinants of use is linear, it is possible (Rao, 1969; Wagstaff, van Doorslaer and Watanabe, 2003; Gravelle, 2003) to use it to decompose the concentration index of use against income as

$$C_{uy} = \frac{b_1\overline{m}}{\overline{u}}C_{my} + \frac{b_2\overline{a}}{\overline{u}}C_{ay} + \frac{b_3\overline{y}}{\overline{u}}C_{yy} + \frac{b_4\overline{e}}{\overline{u}}C_{ey} + \frac{b_5\overline{s}}{\overline{u}}C_{sy} \tag{2}$$

Here m, a, y, e, s denote morbidity, age, income, ethnicity and supply and b_1, b_2 etc are the estimated coefficients on the explanatory variables from the utilisation model. The bars above variables denote means. C_{my} is the concentration index of morbidity against income derived by ranking the population by income and comparing the share of morbidity to people on different ranks with their share of the population. C_{ay}, C_{yy}, C_{ey} and C_{sy} are similarly defined. Note that the concentration index of income against income C_{yy} is just the Gini coefficient for income.

Each of the terms on the right hand side shows the contribution of a variable to overall income related inequality in utilisation as the product of two terms. Consider for example the age term

$$\left(\frac{b_2\overline{a}}{\overline{u}}\right)C_{ay} \tag{3}$$

The first part is the proportion of total use due to age which in a linear model is equivalent to the elasticity of use with respect to age: the percentage change in use caused by a one per cent change in the age. The second term is the concentration index of age against income. It depends on the extent to which age and income are associated (negatively in most general population samples) and the degree of income inequality. It would be zero if either age and income were uncorrelated or if there was no income inequality. Thus the contribution of age to income related inequality in utilisation depends on how responsive utilisation is to age, the degree of association between age and income and the extent of income distribution. Analogous interpretations hold for the other terms in the decomposition (2).

The overall amount of income related inequality is the sum of the contributions of three types of variables: income, other non-need variables, and need variables. This makes the overall concentration index of use against income C_{uy} unsuitable as measure of horizontal *inequity* i.e. of the extent to which use was affected by non-need variables. For example, if only morbidity affected use ($b_1 > 0$, $b_j = 0, j = 2,\ldots,5$) and morbidity was negatively correlated with income ($C_{my} < 0$) then C_{uy} would be negative. For this reason it has been suggested that one should interpret the decomposition (2) as showing how much of total income related inequality in use is (a) not inequity because it is due to the correlation of income with non-need variables, (b) inequity due to the direct effect of income on use and (c) inequity arising from the indirect effect of income via other non-need factors which affect use and are correlated with income (Gravelle, 2003; van Doorslaer, Koolman and Jones, 2002).

3.4 Measuring overall inequality in use

It has recently been suggested, in the context of health rather than use, that rather than seeking to measure differences in health associated with socio-economic characteristics such as income one should measure the overall variation in health across individuals (Murray, Frenk and Gakidou, 2000). The suggestion has attracted critical comment (Braverman, Starfield and Geiger, 2001) but, rather than discuss the arguments in detail and their applicability to use of health care, we prefer to follow the approach in van Doorslaer and Jones (2003). They construct the Gini coefficient of health by ranking individuals by their health and then constructing a Lorenz or concentration curve of cumulated health against the share of the cumulated population. They then decompose the Gini coefficient to show the contribution of each variable to overall inquality in health without having to implicitly privilege one of the variables by using income related inequality.

With the estimated linear utilisation model (1) the Gini coefficient of use can be decomposed as

$$C_{uu} = \frac{b_1\bar{m}}{\bar{u}}C_{mu} + \frac{b_2\bar{a}}{\bar{u}}C_{au} + \frac{b_3\bar{y}}{\bar{u}}C_{yu} + \frac{b_4\bar{e}}{\bar{u}}C_{eu} + \frac{b_5\bar{s}}{\bar{u}}C_{su} + \frac{GC_{ru}}{\bar{u}} \tag{4}$$

where C_{mu}, C_{au} etc are the concentration indices of morbidity, age etc against use. GC_{ru} is the generalised concentration index of the residuals from (1) against use and is defined as $GC_{ru} = 2\text{Cov}(r,F(u))$ where $F(u)$ is the distribution function of use.[6] The utilisation Gini is clearly closely linked to the concentration index of use against income and indeed it can be shown that $C_{uu} = C_{uy}\text{Cov}(u,F(u))/\text{Cov}(u,H(y))$ (Kakwani, 1980). The decomposition of the utilisation Gini shows how much of the overall variation in use is due to need variables and how much is due to non-need variables.

3.5 Non-linear utilisation models

In our data set, utilisation is measured as a binary variable u with u = 1 or 0 depending on whether the individual uses care or not and we estimate a logistic model of the probability of utilisation. Denote the unobservable propensity to use a particular type of health care by

$$u^* = \beta_0 + \beta_1 m + \beta_2 a + \beta_3 y + \beta_4 e + \beta_5 s + v \qquad (5)$$

where the β-parameters are the true values of which the b-parameters are estimates and v is an error term. Suppose that the individual consumes care (u = 1) if and only if $u^* \geq 0$. The probability of use depends on morbidity, age, income etc and the distribution of the error term. If v has a logistic probability density then we have the logistic model and the probability of use is

$$\pi = \Pr[v \leq \beta_0 + \beta_1 m + \beta_2 a + \beta_3 y + \beta_4 e + \beta_5 s] = \frac{e^{\beta_0 + \beta_1 m + \beta_2 a + \beta_3 y + \beta_4 e + \beta_5 s}}{1 + e^{\beta_0 + \beta_1 m + \beta_2 a + \beta_3 y + \beta_4 e + \beta_5 s}} \qquad (6)$$

The coefficients in the propensity equation can be estimated by logistic regression.

The test for horizontal inequity uses the estimated coefficients b_j on the explanatory variables from the logistic model in exactly the same way as in a linear model. For example the marginal effect of a continuous variable such as income on the probability of use is

$$\frac{\partial \pi}{\partial y} = \beta_3 \frac{e^{\beta_0 + \beta_1 m + \beta_2 a + \beta_3 y + \beta_4 e + \beta_5 s}}{\left(1 + e^{\beta_0 + \beta_1 m + \beta_2 a + \beta_3 y + \beta_4 e + \beta_5 s}\right)^2} \qquad (7)$$

The numerator and denominator in the second term on the right hand side in (7) are positive and so the sign of the marginal effect of income on the probability of use is the same as the sign of β_3. Hence examining the sign of the estimated coefficient on income b_3 is a test for horizontal inequity with respect to income.[7]

It would be possible to measure the amount of say income related inequality in the probability of use by estimating probability of use for each individual and then calculating the concentration index of probability of use against income. Similarly it is possible to rank individuals by their estimated probability of use and then to calculate the Gini coefficient to measure overall inequality in probability of use. But with the logistic model the probability of use (6) is not linear in the explanatory variables and so it is not possible to decompose either the concentration index of the probability of use against income or the Gini to show the proportionate contributions from the different types of explanatory variables.

There are three ways in which it is possible to estimate the contributions of the explanatory variables when the utilisation model is non-linear.

(a) For each explanatory variable j calculate the marginal effect (using (7) but with the estimated coefficients b_j replacing the true values β_j) for each individual and take the average over the individuals to get an overall estimated effect $\bar{b}_j$ of the variable. Then calculate the concentration index or the Gini as before in (2) or (4) using $\bar{b}_j$ instead of b_j. van Doorslaer, Koolman and Jones (2002, Tables A1, A3) found that the approximation errors from treating the marginal effects as constant with respect to explanatory variables accounted for 19.7% of the concentration index of the probability of a GP visit with respect to income and 59.5% of the concentration index of the probability of a specialist visit with respect to income.

(b) Express the utilisation variable so that it is linear in the explanatory variables. Thus with the logistic model the log of the estimated odds of use is

$$\hat{u}^* = \ln\left(\frac{p}{1-p}\right) = b_0 + b_1 m + b_2 a + b_3 y + b_4 e + b_5 s \tag{8}$$

where p is the estimated value of the true probability of use π. Then applying the formulae (2) or (4) to $\hat{u}^*$ yields exact decompositions of the concentration index with respect to income and of the Gini. We can interpret $\hat{u}^*$ as the estimated propensity to use health care so that the concentration index or Gini of $\hat{u}^*$ have meaningful and policy relevant interpretations, though perhaps not as transparent as when use is measured in physical units such as the number of visits.

(c) Estimate a Linear Probability Model (LPM), in which the probability of use is linear in the explanatory variables, to obtain the predicted probability

$$p = b_0 + b_1 m + b_2 a + b_3 y + b_4 e + b_5 s \tag{9}$$

Then apply the formulae (2) or (4) to p to give exact decompositions. The obvious problem with this approach is that the LPM can yield estimates of an individual's probability of use which are less than zero or greater than one. Moreover, the estimation procedure yields incorrect standard errors on the coefficients because the residuals from (9) are either $1 - p$ or $-p$ giving rise to heteroscedasticity (Maddala, 1983).

On balance we prefer solution (b) which provides an exact decomposition of the predicted propensity to use health services rather than (a) which may yield seriously inexact decomposition of inequalities in the probability of use or (c) which yields an exact decomposition of an estimated probability of use which can take on nonsense values.

Since our measure of use is the utilisation propensity or the log odds of use, ln (p/1-p), when the probability of use is less than 0.5 the utilisation propensity is negative. This is not a problem for analysis of the effect of variables since a positive coefficient on a variable means it increase the utilisation propensity (makes it less negative). However, the Gini coefficient for any variable x is $C_{xx} = 2\mathrm{Cov}(x, F(x)) / \bar{x}$, where $F(x)$ is the cumulative distribution function for x. The numerator in the definition of the Gini is positive since Cov(x,$F(x)$) must be positive so that the sign of the Gini depends on the sign of the mean of x. In most applications, for example the study of income inequality, $\bar{x}$ is positive. In the current application the mean utilisation propensity is negative because the mean probability of use is less than 0.5 (see below) and the Gini of utilisation propensity would therefore have a negative sign. To preserve the analogy with other applications of inequality measures we multiply the mean utilisation propensity by –1 when calculating both the Gini and the contributions of the various factors to overall inequality as measured by the Gini. This merely changes the sign of the Gini (from negative to positive). It has no effect on the magnitudes of the contributions of the various factors to overall inequality. The interpretation of the signs of the contributions to overall inequality is also still intuitive: a factor with a positive contribution to overall inequality does indeed increase overall inequality.

Similarly, when calculating the extent of income related inequality in the utilisation propensity (the concentration index of utilisation propensity against income), and the contributions of the various factors to it, we multiply the mean utilisation propensity by minus 1. This ensures that pro rich inequality generates a positive concentration index.

3.6 Estimation

We estimated logistic regression models for each of the four types of health care utilisation using STATA v7.0 and used robust standard errors throughout.

For each of the personal characteristic variables we combined similar categories to produce a restricted set of variables. The categories used in the final regression models were the most parsimonious set for which the log-likelihood of the restricted model was not significantly different from the unrestricted model.

To maximise the usable sample size we imputed missing items. For continuous variables, missing values were imputed by regression of the variable on the other explanatory variables using observations with a full set of variables. For categorical variables, missing values were assigned to the most prevalent (omitted) category. To allow for the possibility that items were not missing at random we included dummy variables for each imputed item to indicate item non-response. If the dummy variable is insignificant non-responders' utilisation is affected in the same way as responders by the imputed variable and the imputation has increased sample size without biasing results. If the dummy variable is significant then responders and non-responders are affected in different ways by the item and the dummy enables us to estimate an effect for responders which is not contaminated by the imputation for non-responders.

4 Results

Summary statistics for the variables included in the regression models are presented in Table 1. [8] Sixteen percent of the sample reported at least one GP consultation in the previous two-week period. The figures for day case and outpatient visits are 7% and 29%, respectively. Nine percent of the sample had an inpatient stay in the previous 12 months. Note the relatively high proportion of non-whites in the sample (20%), arising from the boost sample in the 1999 HSE. Note also the high proportion of missing values in the physiological health measures: not all respondents were targeted for measurement in each year and not all of those that were targeted agreed to the nurse visit. Our imputation procedure and inclusion of non-response dummies are attempts to control for the resulting selection effects.

Each of the regression models for the four types of use contains over 200 variables (including the 94 Health Authority dummy variables and the 21 item non response dummies). For clarity of presentation, and ease of comparison across types of health care, we present the results for subsets of variables in Tables 2 to 8. The coefficients reported are from logistic models containing the variables in all the other tables. The coefficients are significant at the 5% level when the absolute value of the z score exceeds 1.9.

4.1 Age, sex and crude self-reported health variables

Two points should be borne in mind in interpreting the effects of age (Table 2). First, the coefficients on the powers of age show their effects on the propensity to use health services as measured by $\ln p/(1-p)$, not on the probability of a visit p. However, the log odds are increasing in the probability and the sign of the effect of variables on the log odds is the same as the sign of their effect on the probability. Hence we can say something about the effect of age on both the probability of use and the log odds of use.

Second, one's intuition about the relationship between age and use may be about the unconditional relationship which does not allow for the fact that many other variables affect use and may be correlated with age. The most obvious example is that health worsens with age. The estimated relationship between propensity to use the health service and age we report is conditional in that it holds non-age factors constant. Hence the conditional relationship may appear "surprising" by reference to intuitions based on the unconditional relationship between age and use.

We also ran cubic unconditional regressions of the utilisation propensities against age powers separately for men and women for all four types of use. The regression results are in Appendix 1. We also graph the conditional and unconditional effect of age on use (see Figure 1 in Appendix 1). The most obvious feature is that the conditional graphs show utilisation as being less responsive to age than the unconditional graphs, which is to be expected since the unconditional graphs reflect the fact that health declines with age.

For men, the unconditional outpatient model has utilisation propensity increasing with age over the entire range of ages. The conditional graph shows utilisation probability declining with age up to 47 years, and then increasing up to age 88 years. For the other three types of utilisation the unconditional and conditional models have utilisation at first declining with age and then increasing before declining in old age.

For women, there is more of a contrast between the conditional and the unconditional models. For GP visits, the unconditional utilisation propensity increases with age whereas the conditional relationship decreases up to age 76. For outpatient visits conditional utilisation declines with age up to 35 years and then increases up to age 70, whereas unconditional utilisation increases up to age 74 and then declines. The age pattern for day cases is similar for the conditional and unconditional models: utilisation propensity at first increases with age (up to age 31 for the conditional model and age 49 for the unconditional model) and declines (up to age 80 for the conditional model and 82 for the unconditional model). For inpatient stays utilisation propensity increases with age over the entire range for the unconditional model but declines up to age 65 and then increases in the conditional model.

Holding all other variables constant, women have lower propensities to use all four types of care, though the effect is smaller and insignificant for outpatient visits. Similar results also hold in the unconditional models. For GP visits, being female reduces the conditional odds of a visit $p/(1-p)$ by about 31% ($\exp(-0.376) = 0.687$). When the probability of use is small this also gives a reasonable approximation for the effect of the categorical variable on the probability of a visit.

The effects of the crude health variables are significant and plausible: worse levels of self reported health are associated with greater utilisation for all types of care and the gradient is steepest for inpatient stays. Individuals with very bad self-reported health are more than twice as likely to consult their GP (exp(0.845) = 2.33) and receive day case treatment (exp(0.812) = 2.25) compared to those with very good health. They are more than three times as likely to have outpatient visits and inpatient stays. Having a limiting longstanding illness also increases use except in the case of GP visits. The number of days cut down is also positively associated with use, although for GP consultations those with 14 days cut down have a lower probability of use than those with 4 to 13 days.

Contextual health measures

There is little evidence of contextual effects of ward level health measures (under 75 SMR, under 75 SIR) on individual utilisation.

4.2 Detailed self-reported health measures

Table 3 shows that individual longstanding illnesses are also positively associated with all types of use, with the sole and plausible exception of the effect of musculoskeletal illness on inpatient stays. Endocrine and metabolic disorders (exp(0.499) = 1.65) and infectious diseases (exp(0.490) = 1.63) have the largest effect on GP visits. Neoplasms have the greatest effect on the probability of outpatient visits and inpatient stays (exp(1.475) = 4.37, exp(1.022) = 2.78). For daycases genitourinary disorders are most important (exp(0.994) =2.70). Worse psycho-social health (captured by the GHQ-12 score) is also generally associated with more use, particularly for GP consultations.

The significant and negative coefficients on the number of longstanding illnesses means that individuals with comorbidity have a lower probability of use than would be expected from addition of the marginal effects of each of the specific illnesses. One explanation for the negative effect of comorbidity on the number of visits is that comorbidities are treated together and so do not require separate visits. It should be borne in mind that the coefficients on the comorbidity variables measure the average effect on use of having two, three or four longstanding illnesses across different combinations of illnesses. A comprehensive treatment of comorbidity effects would delineate fully each feasible combination of longstanding illnesses. We have adopted a more parsimonious count structure that yields only the average effect on use of the different combinations.

4.3 Physiological measures

While few of the physiological variables are significant individually they are jointly significant for all forms of utilisation. The only variables to come through consistently as significant predictors of utilisation are the height variables, with a U-shaped relationship between height and utilisation propensity. For GP consultations, outpatient visits, day case treatment and inpatient stays the propensities are minimised at heights of 1.8 metres, 1.4 metres, 1.6 metres and 1.9 metres, respectively.

Although not individually significant, the pattern of coefficients across BMI indicates that utilisation is lower for more overweight individuals.

4.4 Personal characteristics

Table 5 shows that increases in income lead to fewer GP visits though the coefficient is not significant at the 5% level. For outpatient, day case and inpatient treatment increases in income result in greater utilisation and the effects for outpatient visits and inpatient stays are statistically significant at the 5% level. Thus there is pro-rich inequity for all types of use except GP visits and some evidence for pro-poor inequity in GP visits.

The permanently sick, those with temporary sickness or injury and the retired are more likely to use health services relative to individuals in paid employment, suggesting that the morbidity variables are not picking up all the effects of ill health on use. Those going to school or college full time are less likely to use all types of services. For GP consultations and inpatient stays having a temporary sickness or injury has the largest effect, increasing the probability of use about $\exp(0.811) = 2.25$ and $\exp(0.956) = 2.60$ times respectively. For outpatient visits and day case treatment waiting to take up paid work has the largest effect.

Education has no significant association with inpatient or day case treatment whilst for GP consultations only those with “Other qualifications” have significantly different utilisation propensities from those with a degree. Only for outpatient visits is there much evidence for difference in education to have an effect on utilisation and there is no clear gradient relative to the effect of a degree.

Social class variables are insignificant. We interpret this to mean that social class exerts no independent influence once we have taken account of income, education, and economic activity.

The impact of ethnicity on health service use varies across ethnic groups and types of health care. Non whites seem more likely to consult GPs relative to whites. The probability of a GP visit for Indian, Pakistani and Bangladeshi individuals is around 1.3 times larger. All non-White groups have lower outpatient visit propensities. For Bangladeshis for example the probability of a visit is reduced by about 38% (exp(-0.471) = 0.62). Non-Whites taken together have significantly smaller probabilities of day case treatment, though the individual ethnic categories are not significant. Indian, Bangladeshi and Chinese ethnic groups are less likely to receive inpatient treatment.

4.5 Supply variables

Supply variables have the expected effects on utilisation (Table 6). Individuals are less likely to visit their GP if they live in areas with greater access deprivation. The probability of an outpatient visit is higher the greater the proportion of outpatients who wait less than 26 weeks for an appointment. GP density affects day case treatment positively, possibly reflecting the GPs' gatekeeper role. Hospital distance has a significant and negative effect on the probability of an inpatient stay.

4.6 HA effects

Table 7 shows the variation in the importance of unobserved HA level effects, perhaps reflecting unobserved supply factors not captured in Table 6. The coefficient of variation suggests that unexplained variations in health service use across HAs are widest for day case treatment and narrowest for GP consultations.

Weighted Pearson correlation coefficients between the HA effects for different types of utilisation are shown in the second panel. Unexplained HA variations in GP consultations are positively correlated with unexplained variation in all other types of health care, though the effect is insignificant at the 5% level. The correlation coefficient is highest for outpatient visits and day case treatment (significant at the 5% level) and outpatient visits and inpatient stays. The correlation between day case treatment and inpatient stays is negative, suggesting that there may be substitution between these two types of care, though the effect is insignificant.

4.7 Year effects and missing data indicators

The year effects reported in Table 8 indicate that the conditional probabilities of health care consumption fell over the period for GP consultations and inpatient stays, but increased for outpatient visits and day case treatment.

The item non-response dummy variables are jointly significant in all models. For GP consultations the dummy variables for missing self reported health measures are generally significant. Four of the five missing morbidity items are positively associated with the probability of a GP visit. The coefficients on the dummy variables for missing self reported morbidity variables are not significant in the outpatient, day case and inpatient models.

The coefficients on the item non-response variables for the objective health measures are generally insignificant, which is perhaps surprising given the high proportion of missing values for these variables. It suggests that those with missing objective health measures do not have different levels of utilisation than those without missing values given their health, supply and personal characteristics.

The coefficient on missing income is insignificant in all models and the ethnicity missing item coefficient is insignificant except for inpatient stays. Thus missing data on income and ethnicity do not appear to be affecting their estimated effect on utilisation which is reassuring both for testing for horizontal inequity and for calculating its effect. We also ran a model in which income was interacted with the income non-response dummy variable and found that the coefficient on the interaction was not significant.

5 Decomposition of inequality

The results of the decomposition analysis are summarised in Table 9. The concentration index of use against income and the Gini index of utilisation are presented along with the contribution of the variables to both inequality measures. Due to the large number of variables the results are presented for subsets of variables by summing the contributions of variables within each subset.[9]

To assess the contributions of variables explaining utilisation to inequity, rather than to inequality, requires value judgements to divide the factors into need and non-need variables. The grouping in Table 9 is perhaps relatively uncontroversial as regards most of the variables included in the need and non-need categories though, as we noted in section 3, not everyone would agree that age and gender are need variables if there is a comprehensive set of health variables. The third grouping in the table contains the supply variables about which there is more likelihood of disagreement. It also contains the HA, year, and item non-response dummy variables whose role in inequality is difficult to interpret since they are by construction picking up the effect of unobserved variables which vary systematically across HAs, years, and item non-response.

The cells in the income related inequality columns are the concentration indices of utilisation propensity against income which arise from a subset of variables.[10]

5.1 Income related inequality in use

The concentration index of use against income is negative for GP consultations, outpatient treatment and inpatient treatment, while for day case treatment it is positive but close to zero. These results apparently conflict with the regression results reported in section 4 which show that the poor, other things equal, have more GP visits but fewer outpatient visits, and daycases and inpatient stays. The explanation is that the concentration index of use against income reflects not only the direct effect of income on use but also its indirect effects via the correlation of income with other variables affecting use. As we noted in section 3, in order to measure the extent of horizontal inequity it is imperative that the concentration index of use against income is decomposed to show the contributions of its constituent parts. The amount of horizontal inequity is then measured as the sum of the direct contribution of income and the contributions of non-need variables correlated with income.

For all types of care, the most important factors contributing to income-related health care inequality are the crude self-reported health measures (self-assessed general health, limiting longstanding illness and acute ill health). They increase pro-poor income-related inequality because those in worse self reported health receive more health care and poor health is inversely related to income. Age, gender and the detailed self reported health measures also increase pro-poor inequality. By contrast, the physiological measures tend to generate a pro-rich distribution for all types of health care, except inpatient treatment.

Income itself generates a pro-poor distribution of GP consultations and a pro-rich distribution of secondary care. Education tends to increase the pro-poor distribution of GP visits but lead to pro-rich inequality for secondary care. The rationale is that education groups with higher (lower) average incomes have lower (higher) GP visits but higher (lower) use of secondary care. Ethnicity has a pro-poor effect for GP visits and a pro-rich effect for secondary care use. The non-need variables taken together have a pro-poor contribution to income related inequality in GP visits and pro-rich contributions to income related inequality in secondary care. Their overall contribution is smaller than the contribution of the need variables, except for day case treatment where the contributions are equal and offsetting.

The contributions of the supply variables to income related inequality are small and pro-poor for GP visits and inpatient stays, and pro-rich for outpatient visits. As we noted in section 4 better access, as measured by our supply variables, was associated with greater use of all types, so the differences in the contributions of the supply variables to income related inequality are due to differences in the sign of the correlations of the supply variables with income. Thus the supply variable in the GP use model was an access deprivation measure which is positively correlated with income: richer individuals live in areas with worse access. By contrast richer individuals tend to live in areas with shorter waits for outpatient treatment and so supply tends to produce a pro-rich distribution of outpatient visits.

5.2 Overall inequality

Overall inequality as measured by the Gini coefficient is greatest for outpatient visits (0.44) and GP consultations (0.24). For comparison: the Gini coefficient for income distributions is typically between 0.25 and 0.4.

The contributions of the three different types of variables to the overall level of inequality as measured by the Gini are consistent across all types of use. Need variables make the biggest contribution to overall inequality. Income makes a negligible contribution to the Gini. The other non-need variables do contribute to the Gini but their effect is small relative to the need variables. The year and item non-response variables make a larger contribution to the Gini than the other non-need variables.

There are considerable differences in the relative importance of the factors in explaining income-related inequality and overall inequality in use. Consider for example the relative contributions of crude self-reported health and income: the contribution of crude self reported health to income related inequality in GP visits is nearly twice that of income but its contribution to overall inequality in use is more than 50 times larger than that of income.

6 Conclusion

The English NHS is financed mainly out of general taxation and healthcare is ostensibly free at the point of delivery. The expectation is that need is the driving force behind utilisation and that horizontal equity is achieved. We have demonstrated the existence of horizontal inequities in the utilisation of healthcare in England in terms of income, ethnicity, employment status and education, and that these are important factors driving health care inequality. Low-income individuals and ethnic minorities are more likely to consult their GP but less likely to receive all forms of secondary care. Individuals with lower levels of formal qualifications are generally more likely to consult their GP, but less likely to have day case treatment or inpatient stays. Supply factors contribute relatively little to income-related inequality or to overall inequality in use.

Our results are broadly consistent with those obtained in previous UK studies. Propper and Upward (1992) found a mild pro-poor distribution of NHS expenditure using General Household Survey data on utilisation. More recently a number of studies (van Doorslaer et al, 2000; van Doorslaer, Koolman and Puffer, 2002; van Doorslaer, Koolman and Jones, 2002). also find that low-income individuals have higher use of GP services and lower use of secondary care.

Our findings on ethnicity are also in line with earlier studies (Alexander, 1999; Benzeval and Judge, 1994, 1996; Smaje and Le Grand, 1997) in showing that non-whites tend to consult

GPs more than whites, that there are marked variations in utilisation across non-white groups and that the pattern varies across types of care. As Adamson, Ben Shlomo and Chaturvedi et al's (2003) results suggest, under-utilisation of secondary care by low-income individuals and ethnic minorities does not appear to be caused by a reluctance to seek an initial consultation with a GP. Under-provision of day case and inpatient treatment to low education groups also appears to occur later in the care process.

Unlike other studies we find no effect of social class on utilisation. We suspect that this is because we have a very rich set of health and socio-economic variables so that there is no independent role for social class.

Our analysis goes beyond previous work for a number of reasons. First, we have a rich data-set, allowing us to control for need more comprehensively, examine inequity across a range of personal characteristics, consider the importance of supply factors, and analyse the utilisation of four different types of health care. Second, we use techniques that allow us to test for the existence of inequity and to measure the extent of both income-related and total inequality in health care utilisation.

There are a number of limitations in our study. The first is the utilisation data in the HSE. The hospital based measures take no account of the number of contacts over the twelve month period. For GP consultations there are count data but the limited time period to which these pertain means there is little observed variation in the number of contacts. Further, there is no information on the type, intensity or quality of care provided. Second, the measures of morbidity are predominantly based on self-reported health which may be measured with errors which are correlated with use (Sutton, Carr-Hill, Gravelle et al., 1999). Third, there is a high proportion of missing values for some of the variables included in the models, in particular the physiological health measures. This may be the reason for the lack of explanatory power for the physiological measures in explaining variation in utilisation, though the item non-response dummies are generally insignificant for these variables.

Nevertheless, the paper provides firm evidence on equity in the NHS in England at the start of the millennium. The fact that our findings are generally supportive of earlier studies indicates that that the determinants of utilisation are quite stable over time. Although there are few signs of serious income related inequality in utilisation, we did find evidence of other types of inequity, for example with respect to ethnicity. Since the extent of such inequity varies by particular ethnic group and by stages in the health care process devising policies to correct it may be no easy matter.

Footnotes

[1] See http://www.doh.gov.uk/public/hthsurep.htm for further details about the HSE

[2] Respondents are asked: "How is your health in general? Would you say it was: 'Very good', 'Good', 'Fair', 'Bad', 'Very bad'"

[3] In the survey respondents are asked: "Now I'd like you to think about the two weeks ending yesterday. During those two weeks did you have to cut down on any of the things you usually do about the house or at work or in your free time because of illness or injury?" If the reply is yes respondents are then asked: "How many days was this in all during these 2 weeks, including Saturdays and Sundays?: '1-3 days', '4-6 days', 7-13 days', '14 days'"

[4] Respondents are asked: "Do you have any longstanding illness, disability or infirmity? By longstanding I mean anything that has troubled you over a period of time or is likely to affect you over a period of time?" If they answer yes they are then asked for up to six illnesses that affect them in this way by broad disease code.

[5] The IMD access domain score is a measure of access deprivation in which higher values of the score represent higher levels of deprivation. One component of the score is access to a GP surgery.

[6] The reason that a similar term $GC_{ry} = 2\mathrm{Cov}(r,H(y))$, where H is the cumulative distribution function for income, does not appear in the decomposition of C_{uy} in (2) is that GC_{ry} has a probability limit of zero (Gravelle, 2003). By contrast GC_{ru} does not vanish asymptotically and its size depends on the goodness of fit of the estimated utilisation model.

[7] For a dummy variable D the marginal effect is given by

$$\Pr(u = 1 | z, D = 1) - \Pr(u = 1 | z, D = 0)$$

where z is a vector of the other regressors in the model. The marginal effect also has the same sign as the coefficient on D.

[8] The sample means are those for individuals in the sample with non-missing data on GP consultations (n=50,968).

[9] See Appendix 2 for the detailed decompositions of income-related and overall inequality in utilisation.

[10] In terms of Gravelle (2003) the cells in the income row give the partial concentration index of use against income and, in a given column, the sum of the cells in the income row and the other non-need variable row gives the augmented partial concentration index.

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Table 1. Summary statistics of variables included in the regression models

Variable	Mean	S.D.
Health service utilisation		
GP consultations	0.157	0.364
Outpatient visits	0.290	0.454
Day case treatment	0.065	0.247
Inpatient stays	0.091	0.287
Age and sex		
Female	0.543	0.498
Age (years/100)	0.399	0.243
Year		
1998	0.385	0.487
1999	0.371	0.483
2000	0.244	0.429
Self-reported general health		
Very good	0.347	0.476
Good	0.399	0.490
Fair	0.171	0.376
Bad	0.045	0.208
Very bad	0.013	0.113
Limiting longstanding illness	0.219	0.414
Days cut down		
0 days	0.823	0.382
1 to 3 days	0.050	0.217
4 to 6 days	0.025	0.155
7 to 13 days	0.025	0.156
14 days	0.052	0.223
Type of longstanding illness		
Neoplasms	0.013	0.112
Endocrine and metabolic	0.046	0.209
Mental disorder	0.037	0.189
Nervous system	0.036	0.187
Eye	0.023	0.151
Ear	0.023	0.149
Heart and circulatory	0.095	0.293
Respiratory	0.096	0.295
Digestive	0.041	0.198
Genitourinary	0.011	0.105
Reproductive	0.009	0.096
Musculoskeletal	0.152	0.359
Infectious disease	0.002	0.041
Blood disorders	0.007	0.081
Skin	0.023	0.150
Other	0.005	0.073
No. longstanding illnesses		
0	0.598	0.490
1	0.251	0.434
2	0.101	0.302
3	0.036	0.186
4 or more	0.013	0.115

Variable	Mean	S.D.
GHQ-12 score		
0	0.439	0.496
1	0.104	0.306
2	0.059	0.236
3	0.038	0.192
4	0.027	0.162
5	0.021	0.142
6	0.015	0.123
7	0.013	0.113
8	0.010	0.101
9	0.009	0.094
10	0.009	0.093
11	0.007	0.086
12	0.008	0.088
Physiological measures		
Height	1.587	0.200
Weight	64.442	21.954
Systolic blood pressure	129.149	18.880
Total cholesterol	5.054	1.009
HDL cholesterol	1.425	0.258
Haemoglobin	13.724	1.051
Fibrinogen	2.749	0.535
Ferritin	70.524	60.483
Waist:Hip ratio	0.829	0.084
Body mass index		
<20	0.185	0.389
20-25	0.279	0.449
25-30	0.262	0.440
30-35	0.099	0.299
35-40	0.026	0.159
>40	0.008	0.091
Ward-level health variables		
SMR (aged<75 years)	106.051	29.271
SIR (aged<75 years)	104.402	32.260
ln(Income)	9.537	0.840
Social class of head of household		
I, II	0.323	0.468
IIIN, IIIM	0.392	0.488
IV, V or other	0.234	0.423
Economic activity		
In paid employment	0.397	0.489
Going to school or college full time	0.044	0.204
Permanent long-term sickness	0.032	0.177
Retired from paid work	0.143	0.350
Looking after the home	0.097	0.296
Waiting to take up paid work	0.002	0.044
Looking for paid work	0.019	0.137
Temporary sickness or injury	0.003	0.055
Doing something else	0.004	0.062

Variable	Mean	S.D.
Education		
Degree	0.101	0.301
Higher education less than a degree	0.078	0.268
A level or equivalent	0.080	0.271
GCSE or CSE or equivalent	0.208	0.406
Other qualification	0.035	0.183
No qualification	0.262	0.440
Ethnic group		
White	0.761	0.426
Black	0.047	0.212
Indian	0.043	0.204
Pakistani	0.045	0.208
Bangladeshi	0.039	0.193
Chinese	0.018	0.134
Other non-white ethnic group	0.019	0.137
Supply variables		
Access domain score	-0.426	0.717
Prop. outpatients seen<26 weeks	0.939	0.030
GPs per 1000 patients	0.570	0.087
Average distance to acute providers	22.624	11.606
Item non-response variables		
Self-reported general health	0.025	0.157
Limiting longstanding illness	0.025	0.157
Days cut down	0.025	0.157
Type of longstanding illness	0.000	0.017
GHQ-12 score	0.240	0.427
Height	0.097	0.296
Weight	0.133	0.340
Systolic blood pressure	0.419	0.493
Total cholesterol	0.698	0.459
HDL cholesterol	0.700	0.458
Ferritin	0.702	0.457
Haemoglobin	0.697	0.459
Fibrinogen	0.739	0.439
Waist:Hip ratio	0.619	0.486
Body Mass Index	0.139	0.346
Ward	0.001	0.027
Income	0.209	0.407
Social class of head of household	0.050	0.219
Economic activity	0.259	0.438
Education	0.237	0.425
Ethnic group	0.027	0.161

Table 2. Effect of age, sex and crude self-reported health measures on health service utilisation

	GP consultations		Outpatient visits		Day case treatment		Inpatient stays	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Constant	5.382	2.67	-2.779	-1.54	2.735	0.97	-3.319	-1.20
Age and sex variables								
Age [a]	-8.169	-4.44	-5.750	-3.98	-3.123	-1.20	-9.432	-4.13
Age squared	17.179	4.56	9.360	3.16	6.353	1.22	15.841	3.45
Age cubed	-10.131	-4.26	-4.621	-2.45	-3.640	-1.12	-7.635	-2.69
Female	-0.376	-2.71	-0.145	-1.28	-0.918	-4.12	-0.659	-3.49
Female*Age	7.609	5.81	-0.917	-0.87	7.612	3.92	7.907	4.72
Female*Age squared	-17.518	-5.63	4.811	1.92	-16.309	-3.64	-19.211	-4.99
Female*Age cubed	10.755	5.00	-4.314	-2.47	9.612	3.16	12.286	4.77
Crude self-reported health measures								
Self-reported general health [b]								
Good	0.294	8.23	0.220	8.28	0.206	4.02	0.197	4.15
Fair	0.570	12.16	0.580	15.94	0.457	6.81	0.485	8.07
Bad	0.636	8.90	0.863	14.21	0.712	7.65	0.607	7.11
Very bad	0.845	7.90	1.109	10.66	0.812	6.09	1.164	10.10
Limiting longstanding illness	-0.101	-2.20	0.180	4.97	0.107	1.74	0.293	5.18
Days cut down [c]								
1 to 3 days	0.990	19.40	0.250	5.32	0.257	3.32	-0.008	-0.10
4 to 6 days	1.381	20.51	0.409	6.34	0.424	4.50	0.370	4.13
7 to 13 days	1.620	24.51	0.464	7.31	0.346	3.55	0.511	6.18
14 days	1.286	24.85	0.639	12.88	0.409	5.78	0.797	13.24
Ward-level health variables								
SMR (aged<75 years)	-0.0001	-0.08	0.001	2.11	0.001	0.55	0.001	1.00
SIR (aged<75 years)	-0.001	-1.45	-0.001	-1.97	-0.003	-2.38	-0.001	-0.80
Tests of restrictions								
Age and sex variables=0	$\chi^2_{(7)}$=62.01, p<0.0001		$\chi^2_{(7)}$=51.87, p<0.0001		$\chi^2_{(7)}$=28.64, p=0.0002		$\chi^2_{(7)}$=77.50, p<0.0001	
Crude self-reported health measures=0	$\chi^2_{(9)}$=1868.36, p<0.0001		$\chi^2_{(9)}$=813.41, p<0.0001		$\chi^2_{(9)}$=173.39, p<0.0001		$\chi^2_{(9)}$=490.94, p<0.0001	
N	50968		50922		50927		50932	
Initial Log-likelihood	-22191		-30676		-12258		-15481	
Model log likelihood	-19477		-27490		-11464		-13477	
Pseudo-R^2	0.1223		0.1038		0.0648		0.1295	

[a] Age/100.
[b] The baseline category is "Very good".
[c] The baseline category is zero days.

Table 3. Effect of detailed self-reported health measures on health service utilisation

	GP consultations		Outpatient visits		Day case treatment		Inpatient stays	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Type of longstanding illness								
Neoplasms	0.319	3.06	1.475	15.21	0.919	7.44	1.022	9.60
Endocrine and metabolic	0.499	7.64	0.749	13.59	0.324	3.68	0.188	2.34
Mental disorder	0.313	4.21	0.230	3.50	0.084	0.79	0.067	0.76
Nervous system	0.245	3.42	0.411	6.81	0.307	3.22	0.098	1.13
Eye	0.017	0.18	0.829	11.47	0.496	4.33	0.100	0.98
Ear	0.142	1.61	0.557	7.70	0.457	4.09	0.021	0.19
Heart and circulatory	0.419	7.40	0.496	10.70	0.196	2.48	0.440	6.55
Respiratory	0.394	7.95	0.306	7.53	0.214	3.05	0.200	3.12
Digestive	0.333	4.81	0.614	10.76	0.612	7.00	0.276	3.35
Genitourinary	0.394	3.52	0.974	9.89	0.994	7.86	0.575	4.65
Reproductive	0.267	2.21	0.621	5.82	0.774	5.56	0.390	2.80
Musculoskeletal	0.168	3.15	0.413	9.85	0.239	3.32	-0.107	-1.63
Infectious disease	0.490	1.80	0.254	1.03	0.098	0.26	0.293	0.91
Blood disorders	0.346	2.46	0.797	6.50	0.682	3.96	0.366	2.36
Skin	0.402	4.77	0.503	7.21	0.347	2.95	0.066	0.60
Other	0.314	1.94	0.263	1.90	0.245	1.11	0.074	0.36
Number of longstanding illnesses [a]								
2	-0.162	-2.53	-0.339	-6.47	-0.045	-0.52	-0.099	-1.26
3	-0.437	-4.12	-0.656	-7.45	-0.545	-3.79	-0.226	-1.76
4 or more	-0.838	-5.13	-1.225	-8.95	-0.838	-3.75	-0.527	-2.63
GHQ-12 score [b]								
1	0.173	3.76	0.058	1.62	0.177	2.90	0.198	3.48
2	0.214	3.78	0.112	2.50	-0.110	-1.34	0.293	4.34
3	0.272	4.22	0.110	2.02	0.047	0.51	0.307	3.88
4	0.386	5.27	0.192	3.06	0.311	3.20	0.469	5.40
5	0.398	4.75	0.175	2.45	0.114	1.00	0.171	1.66
6	0.129	1.28	0.329	4.09	0.054	0.40	0.320	2.91
7	0.315	3.11	0.120	1.34	-0.154	-1.02	0.174	1.39
8	0.248	2.12	0.280	2.78	0.194	1.28	0.431	3.23
9	0.414	3.48	0.274	2.53	0.303	2.01	0.337	2.41
10	0.382	3.12	0.193	1.79	0.243	1.63	0.579	4.37
11	0.398	3.00	0.427	3.53	0.339	2.08	0.421	2.91
12	0.437	3.44	0.241	2.07	0.359	2.34	0.274	1.89
Test of restrictions								
Detailed self-reported health measures=0	$\chi^2_{(32)}$=265.40, p<0.0001		$\chi^2_{(32)}$=775.62, p<0.0001		$\chi^2_{(32)}$=242.24, p<0.0001		$\chi^2_{(32)}$=285.78, p<0.0001	

[a] The baseline category is 0 or 1.
[b] The baseline category is 0

Table 4. Effect of physiological measures on health service utilisation

	GP consultations		Outpatient visits		Day case treatment		Inpatient stays	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Physiological measures								
Height	-3.917	-3.55	-2.565	-2.78	-5.168	-3.14	-4.516	-2.92
Height squared	1.085	2.96	0.906	2.99	1.658	3.11	1.209	2.40
Weight	0.013	1.77	0.004	0.71	0.007	0.62	0.017	1.64
Weight squared	-0.0001	-1.27	-0.00001	-0.22	-0.0001	-1.02	-0.00005	-0.79
Systolic blood pressure	-0.002	-0.28	-0.001	-0.17	-0.009	-0.82	-0.026	-2.76
Systolic blood pressure squared	-0.000002	-0.07	-0.000005	-0.23	0.00002	0.50	0.0001	2.28
Total cholesterol	-0.080	-0.63	-0.081	-0.78	0.232	1.15	0.029	0.19
Total cholesterol squared	0.008	0.77	0.004	0.42	-0.018	-1.04	-0.004	-0.32
HDL cholesterol	-0.054	-0.82	0.038	0.77	-0.018	-0.20	0.058	0.77
Haemoglobin	0.118	0.68	-0.047	-0.33	-0.073	-0.29	0.347	1.62
Haemoglobin squared	-0.006	-0.86	0.000	0.06	0.001	0.14	-0.018	-2.19
Fibrinogen	-0.325	-2.59	-0.138	-1.28	0.190	0.77	0.020	0.12
Fibrinogen squared	0.050	2.87	0.027	1.71	-0.026	-0.68	0.0002	0.01
Ferritin	0.0004	1.01	0.0003	0.98	-0.0002	-0.29	0.00001	0.02
Ferritin squared	-0.00000001	-0.07	-0.00000001	-0.05	0.0000002	0.88	0.0000002	0.62
Waist:Hip ratio	-9.054	-2.61	7.476	2.51	-4.309	-0.95	9.804	1.95
Waist:Hip ratio squared	5.594	2.83	-4.179	-2.45	2.416	0.94	-4.916	-1.73
Body Mass Index [a]								
<20	-0.008	-0.12	-0.109	-2.20	-0.142	-1.60	0.053	0.63
25-30	-0.048	-0.97	-0.036	-0.90	0.036	0.53	-0.117	-1.84
30-35	-0.074	-0.87	-0.069	-1.00	0.022	0.19	-0.128	-1.21
35-40	-0.144	-1.05	-0.033	-0.30	-0.044	-0.23	-0.523	-3.03
>40	-0.183	-0.87	-0.279	-1.60	-0.071	-0.25	-0.461	-1.80
Test of restrictions								
Objective health measures=0	$\chi^2_{(24)}$=60.59, p=0.0001		$\chi^2_{(24)}$=78.20, p<0.0001		$\chi^2_{(24)}$=42.86, p=0.0103		$\chi^2_{(24)}$=97.44, p<0.0001	

[a] The baseline category is 20-25.

Table 5. Effect of socio-economic variables and ethnicity on health service utilisation

	GP consultations		Outpatient visits		Day case treatment		Inpatient stays	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
ln(Income)	-0.036	-1.75	0.041	2.33	0.047	1.58	0.075	2.76
Social class of head of household [a]								
IIIN, IIIM	0.036	1.00	0.027	0.96	0.053	1.07	0.067	1.45
IV, V or other	0.082	1.95	0.015	0.45	0.030	0.51	0.086	1.61
Economic activity [b]								
Going to school or college full time	-0.249	-2.86	-0.195	-3.03	-0.447	-3.32	-0.543	-4.26
Permanent long-term sickness	0.152	2.01	0.350	5.27	0.253	2.73	0.618	7.09
Retired from paid work	0.106	1.66	0.115	2.28	0.074	0.85	0.621	7.81
Looking after the home	0.144	2.85	-0.134	-3.12	0.001	0.02	0.637	10.00
Waiting to take up paid work	0.267	0.95	0.505	2.40	0.577	1.78	0.224	0.58
Looking for paid work	-0.168	-1.54	-0.133	-1.66	-0.045	-0.31	0.170	1.26
Temporary sickness or injury	0.811	4.11	0.407	2.21	0.270	1.04	0.956	4.33
Doing something else	0.033	0.16	-0.031	-0.18	0.089	0.31	0.676	3.08
Education [c]								
Higher education less than a degree	-0.009	-0.13	0.131	2.59	0.080	0.92	0.118	1.41
A level or equivalent	0.054	0.79	0.081	1.58	0.022	0.24	0.014	0.16
GCSE or CSE or equivalent	0.103	1.79	0.143	3.30	0.064	0.84	0.034	0.48
Other qualification	0.254	3.02	0.208	3.13	0.097	0.86	-0.005	-0.05
No qualification	0.111	1.81	0.054	1.15	-0.086	-1.04	-0.066	-0.86
Ethnic group [d]								
Black	0.083	1.15	-0.108	-1.86	-0.014	-0.14	-0.120	-1.29
Indian	0.253	3.62	-0.227	-3.81	-0.186	-1.72	-0.225	-2.26
Pakistani	0.291	3.94	-0.461	-7.11	-0.127	-1.12	0.016	0.17
Bangladeshi	0.238	2.54	-0.471	-6.01	-0.124	-0.91	-0.527	-3.87
Chinese	0.017	0.15	-0.595	-6.08	-0.023	-0.15	-0.474	-2.72
Other non-white ethnic group	0.062	0.60	-0.118	-1.43	0.018	0.13	-0.063	-0.45
Test of restrictions								
Non-income socio-economic and ethnicity variables=0	$\chi^2_{(21)}$=89.50, p<0.0001		$\chi^2_{(21)}$=214.16, p<0.0001		$\chi^2_{(21)}$=41.42, p=0.0050		$\chi^2_{(21)}$=230.56, p<0.0001	

[a] The baseline category is I and II.
[b] The baseline category is In paid employment.
[c] The baseline category is Degree.
[d] The baseline category is White.

Table 6. Effect of supply on health service utilisation [a]

	GP consultations		Outpatient treatment		Day case treatment		Inpatient stays	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Access domain score	-0.059	-2.13						
Proportion of outpatients seen<26 weeks			1.447	2.17				
GPs per 1000 patients					0.398	1.71		
Average distance to acute providers							-0.005	-2.08
Test of restrictions								
Supply variables including HA effects=0	$\chi^2_{(95)}$=155.75, p=0.0001		$\chi^2_{(95)}$=172.35, p<0.0001		$\chi^2_{(95)}$=121.19, p=0.0362		$\chi^2_{(95)}$=107.06, p=0.1872	

[a] The models also include HA effects (see Table 7).

Table 7. HA effects [a]

	GP consultations	Outpatient visits	Day case treatment	Inpatient stays
Distributions				
Standard deviation	0.169	0.140	0.210	0.179
Coefficient of variation	0.031	0.048	0.073	0.054
Range	0.898	0.709	1.130	0.994
Decile range	0.447	0.359	0.505	0.440
Inter-quartile range	0.252	0.204	0.256	0.179
Correlation coefficients				
Outpatient visits	0.082	1.000		
Day case treatment	0.014	0.214 [b]	1.000	
Inpatient stays	0.078	0.162	-0.009	1.000

[a] The HA effect of the baseline is the constant term and the HA effects for the other HAs are measured as the coefficient on the HA dummy variable plus the constant term. The effect of each HA is weighted by the proportion of the sample in that HA.
[b] Significant at the 5% level.

Table 8. Effect of year and item non-response on health service utilisation

	GP consultations		Outpatient visits		Day case treatment		Inpatient stays	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Year effects [a]								
1999	-0.111	-2.78	0.236	7.30	0.282	4.97	0.013	0.26
2000	-0.117	-2.46	0.287	7.63	0.301	4.51	-0.100	-1.69
Item non-response variables								
Self-reported general health	1.684	2.53	-0.331	-0.45	-0.187	-0.23	-0.389	-0.39
Limiting longstanding illness	-2.239	-2.72	0.894	0.95	-0.492	-0.41	0.489	0.36
Days cut down	1.521	3.22	-0.241	-0.44	0.775	1.43	0.499	0.96
Type of longstanding illness	3.657	4.65	-0.714	-0.64	0.720	0.40	-0.741	-0.34
GHQ-12 score	0.100	1.90	-0.057	-1.31	-0.065	-0.85	0.000	0.01
Height	-0.159	-1.94	-0.108	-1.56	-0.202	-1.75	0.148	1.49
Weight	0.211	1.14	-0.153	-0.98	0.196	0.73	0.040	0.22
Systolic blood pressure	-0.061	-1.35	0.088	2.48	0.002	0.04	-0.061	-1.04
Total cholesterol	0.634	2.07	0.228	1.03	-0.211	-0.62	-0.278	-0.90
HDL cholesterol	-0.403	-1.36	-0.119	-0.57	0.514	1.62	0.355	1.22
Ferritin	-0.104	-0.78	-0.022	-0.21	-0.252	-1.27	-0.024	-0.15
Haemoglobin	-0.057	-0.44	0.002	0.02	0.049	0.25	0.218	1.40
Fibrinogen	0.037	0.52	-0.045	-0.78	0.000	0.00	-0.102	-1.12
Waist:Hip ratio	0.064	1.18	-0.324	-7.46	-0.071	-0.95	-0.104	-1.59
Body Mass Index	-0.078	-0.39	0.154	0.93	-0.066	-0.23	0.082	0.40
Ward	0.717	1.69	0.114	0.28	-0.620	-0.59	-0.152	-0.22
Income	0.006	0.16	-0.033	-1.09	0.030	0.58	-0.033	-0.71
Social class of head of household	0.719	3.55	0.130	0.63	0.390	1.15	1.222	4.30
Economic activity	-0.575	-2.84	-0.020	-0.10	-0.286	-0.84	-0.046	-0.15
Education	0.131	0.61	-0.368	-1.81	-0.159	-0.45	-1.006	-3.10
Ethnic group	0.183	0.55	0.409	1.47	0.439	1.00	0.751	1.99
Test of restrictions								
Year effects=0	$\chi^2_{(2)}$=9.89, p=0.0071		$\chi^2_{(2)}$=78.42, p<0.0001		$\chi^2_{(2)}$=31.42, p<0.0001		$\chi^2_{(2)}$=3.94, p=0.1394	
Item non-response variables=0	$\chi^2_{(21)}$=240.88, p<0.0001		$\chi^2_{(21)}$=141.05, p<0.0001		$\chi^2_{(21)}$=31.34, p=0.0682		$\chi^2_{(21)}$=233.25, p<0.0001	

[a] The baseline category is 1998

Table 9. Decomposition of income-related and overall inequality in utilisation [a]

	GP consultations		Outpatient visits		Day case treatment		Inpatient stays	
	Income-related inequality (pro poor)	Overall inequality	Income-related inequality (pro poor)	Overall inequality	Income-related inequality (pro rich)	Overall inequality	Income-related inequality (pro poor)	Overall inequality
Total	-0.067	0.243	-0.028	0.440	0.001	0.128	-0.033	0.187
Arising from								
Age and sex variables	-0.011	0.020	-0.017	-0.041	0.001	0.003	-0.012	-0.018
Crude self-reported health measures	-0.017	0.114	-0.042	0.168	-0.011	0.039	-0.016	0.056
Detailed self-reported health measures	-0.007	0.048	-0.024	0.160	-0.005	0.037	-0.003	0.028
Objective health measures	0.004	0.004	0.011	0.019	0.005	0.001	-0.003	0.013
Not working due to ill health [b]	-0.003	0.005	-0.008	0.018	-0.002	0.003	-0.009	0.022
All need variables	-0.034	0.190	-0.080	0.323	-0.012	0.083	-0.044	0.100
ln(Income)	-0.009	0.002	0.019	0.000	0.008	0.000	0.013	-0.002
Social class of head of household	-0.004	0.001	-0.002	0.000	-0.002	0.000	-0.003	0.000
Economic activity [c]	0.000	0.004	0.006	0.003	0.001	0.003	-0.006	0.015
Education	-0.003	0.005	0.002	0.009	0.003	0.000	0.003	-0.001
Ethnic group	-0.007	0.002	0.023	0.023	0.002	0.001	0.006	0.005
All non need variables	-0.022	0.014	0.048	0.035	0.012	0.005	0.012	0.016
Supply variables	-0.003	0.001	0.001	0.001	0.000	0.000	-0.001	0.000
HA effects	-0.002	0.011	-0.003	0.015	-0.001	0.013	0.002	0.007
Year effects	0.001	0.000	-0.003	0.005	-0.001	0.006	-0.001	-0.001
Item non-response variables	-0.005	0.027	0.008	0.061	0.003	0.021	-0.001	0.064
All other variable	-0.009	0.039	0.003	0.082	0.001	0.040	-0.001	0.070

[a] The concentration index of use against income (income-related inequality) and the Gini index of utilisation (overall inequality) have both been multiplied by –1 to allow for the fact that the mean of the utilisation variable is negative because the probability of utilisation is less than ½. This ensures that the elasticity of utilisation with respect to a variable is positive if the variable increases utilisation. It also ensures that, as is conventional, the income related inequality measures are positive if there is pro rich income related inequality and that the Gini coefficient is positive. The decompositions in each column may not sum to the total due to rounding error.

[b] Includes the economic inactivity variables that are health-related (permanent long-term sickness, retired from paid work, temporary sickness or injury)

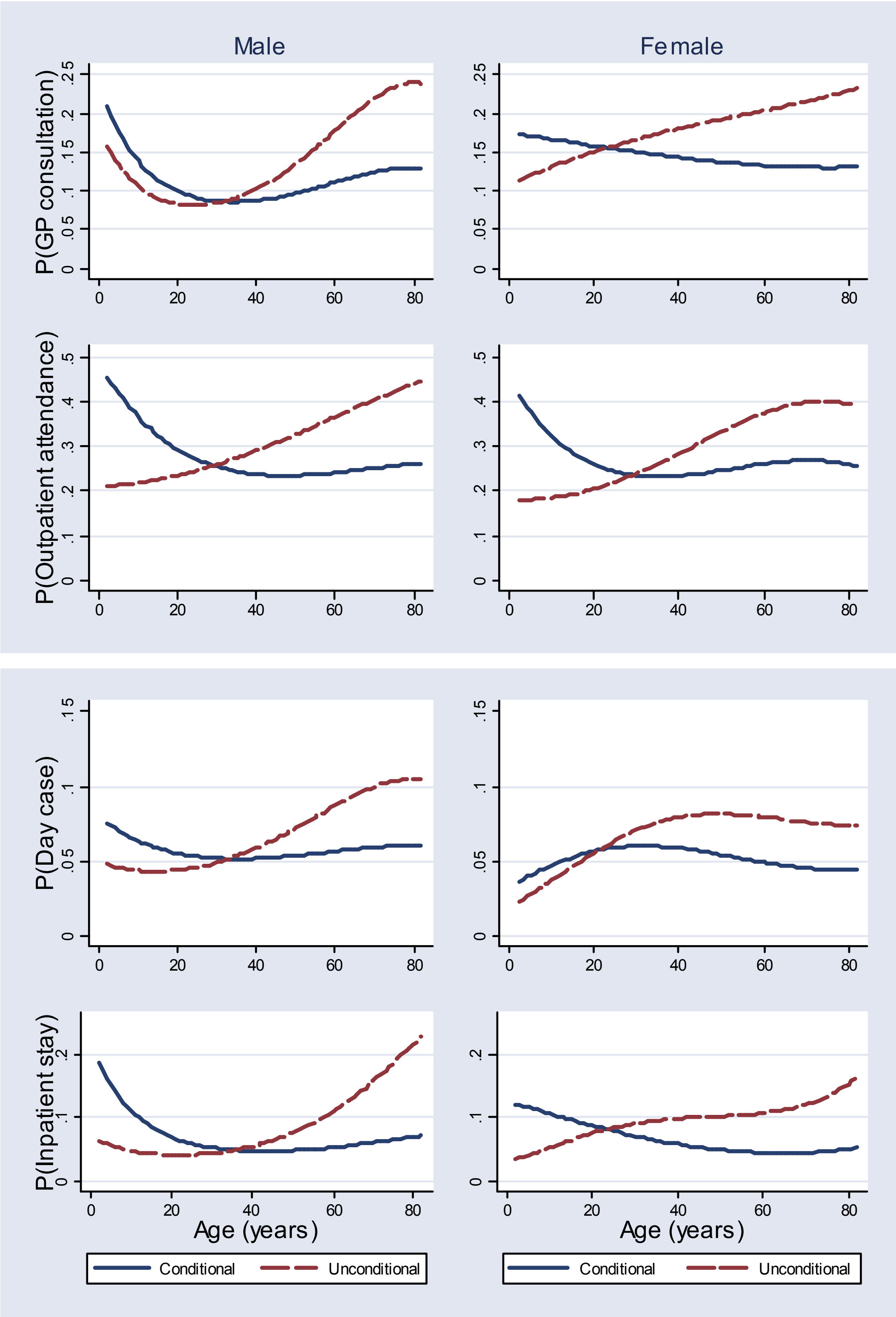
[c] Includes the non-health related economic activity variables only (going to school or college full-time, looking after the home, waiting to take up paid work, looking for paid work, and doing something else)

Appendix 1

Table A1. Unconditional effects of age on health service utilisation

	GP consultations		Outpatient treatment		Day case treatment		Inpatient stays	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Males								
Age	-8.318	-11.09	0.188	0.33	-2.338	-2.14	-5.682	-5.78
Age squared	22.345	11.37	2.929	1.95	9.690	3.47	15.946	6.54
Age cubed	-14.241	-9.83	-1.852	-1.66	-6.882	-3.38	-8.488	-4.94
Constant	-1.514	-20.84	-1.320	-22.36	-2.952	-25.79	-2.594	-25.06
N	23,316		23,301		23,307		23,305	
Initial log-likelihood	-9105.3		-14145.1		-5509.22		-6490.86	
Model log-likelihood	-8874.05		-13857.5		-5426.02		-6115.65	
Pseudo-R2	0.0254		0.0203		0.0151		0.0578	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Females								
Age	2.296	3.70	-0.510	-0.96	7.530	7.06	7.821	8.97
Age squared	-2.723	-1.82	7.371	5.66	-12.277	-4.93	-15.625	-7.89
Age cubed	1.536	1.48	-6.328	-6.96	6.256	3.68	10.888	8.29
Constant	-2.096	-29.20	-1.498	-24.52	-3.902	-29.21	-3.541	-31.8
N	27,652		27,621		27,620		27,627	
Initial log-likelihood	-12981.2		-16527.8		-6748.24		-8959.74	
Model log-likelihood	-12863.6		-16118.3		-6669.26		-8691.16	
Pseudo-R2	0.0091		0.0248		0.0117		0.03	

Figure 1. Conditional and unconditional relationships between age and probability of use.



Note: Conditional: results from multiple regression with cubic function of age and all other variables. Unconditional: results from regression with powers of age only.

Appendix 2

Table A2. Detailed decomposition of income-related and overall inequality in utilisation

	GP consultations		Outpatient treatment		Day case treatment		Inpatient stays	
	Income-related inequality	Overall inequality	Income-related inequality	Overall inequality	Income-related inequality	Overall inequality	Income-related inequality	Overall inequality
Age and sex variables								
Age	0.034	-0.189	0.046	-0.376	0.009	-0.065	0.028	-0.251
Age squared	-0.150	0.383	-0.157	0.511	-0.037	0.102	-0.100	0.385
Age cubed	0.100	-0.188	0.088	-0.191	0.024	-0.042	0.054	-0.153
Female	0.003	-0.017	0.002	0.002	0.005	-0.004	0.004	-0.014
Female*Age	-0.056	0.222	0.013	-0.030	-0.037	0.097	-0.042	0.181
Female*Age squared	0.146	-0.349	-0.077	0.142	0.090	-0.141	0.115	-0.331
Female*Age cubed	-0.088	0.157	0.068	-0.099	-0.052	0.056	-0.072	0.165
Sub-total	-0.011	0.020	-0.017	-0.041	0.001	0.003	-0.012	-0.018
Crude self-reported health measures								
Self-reported general health								
Good	0.002	0.000	0.003	-0.003	0.001	0.000	0.001	-0.002
Fair	-0.008	0.025	-0.016	0.054	-0.004	0.012	-0.005	0.014
Bad	-0.005	0.011	-0.013	0.032	-0.004	0.009	-0.003	0.008
Very bad	-0.002	0.005	-0.005	0.013	-0.001	0.003	-0.002	0.005
Limiting longstanding illness	0.002	-0.006	-0.006	0.027	-0.001	0.005	-0.004	0.013
Days cut down								
1 to 3 days	0.002	0.016	0.001	0.004	0.000	0.001	0.000	0.000
4 to 6 days	-0.001	0.014	-0.001	0.006	0.000	0.002	0.000	0.002
7 to 13 days	-0.002	0.019	-0.001	0.007	0.000	0.002	0.000	0.003
14 days	-0.005	0.030	-0.005	0.027	-0.001	0.005	-0.002	0.013
Sub-total	-0.017	0.114	-0.042	0.168	-0.011	0.039	-0.016	0.056
Type of longstanding illness								
Neoplasms	0.000	0.001	-0.002	0.017	0.000	0.004	0.000	0.004
Endocrine and metabolic	-0.001	0.007	-0.004	0.025	-0.001	0.003	0.000	0.002
Mental disorder	-0.002	0.004	-0.002	0.004	0.000	0.000	0.000	0.001
Nervous system	0.000	0.002	-0.001	0.009	0.000	0.002	0.000	0.001
Eye	0.000	0.000	-0.004	0.014	-0.001	0.002	0.000	0.000
Ear	0.000	0.000	-0.002	0.008	-0.001	0.002	0.000	0.000
Heart and circulatory	-0.003	0.012	-0.007	0.031	-0.001	0.003	-0.002	0.010
Respiratory	-0.001	0.008	-0.002	0.012	-0.001	0.002	-0.001	0.002
Digestive	-0.001	0.004	-0.002	0.017	-0.001	0.006	0.000	0.002
Genitourinary	0.000	0.001	-0.002	0.009	-0.001	0.003	0.000	0.002
Reproductive	0.000	0.001	0.000	0.004	0.000	0.002	0.000	0.001
Musculoskeletal	-0.001	0.005	-0.007	0.039	-0.001	0.006	0.001	-0.003
Infectious disease	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Blood disorders	0.000	0.001	-0.001	0.004	0.000	0.001	0.000	0.001
Skin	0.000	0.002	-0.001	0.005	0.000	0.001	0.000	0.000
Other	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Number of longstanding illnesses								

2	0.001	-0.005	0.005	-0.022	0.000	-0.001	0.001	-0.002
3	0.002	-0.005	0.005	-0.019	0.002	-0.004	0.001	-0.002
4 or more	0.002	-0.004	0.005	-0.014	0.001	-0.003	0.001	-0.002
GHQ-12 score								
1	0.001	0.001	0.000	0.001	0.000	0.002	0.000	0.001
2	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.002
3	0.000	0.002	0.000	0.001	0.000	0.000	0.000	0.001
4	0.000	0.002	0.000	0.002	0.000	0.001	0.000	0.002
5	0.000	0.002	0.000	0.001	0.000	0.000	0.000	0.000
6	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.001
7	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000
8	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.001
9	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
10	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.001
11	0.000	0.001	0.000	0.002	0.000	0.001	0.000	0.001
12	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.000
Sub-total	-0.007	0.048	-0.024	0.160	-0.005	0.037	-0.003	0.028
Physiological measures								
Height	-0.038	0.025	-0.048	-0.073	-0.034	-0.044	-0.032	-0.017
Height squared	0.033	-0.022	0.053	0.076	0.033	0.041	0.026	0.012
Weight	0.013	0.003	0.008	0.020	0.004	0.009	0.011	0.016
Weight squared	-0.007	-0.001	-0.002	-0.004	-0.005	-0.009	-0.004	-0.005
Systolic blood pressure	0.001	-0.002	0.001	-0.004	0.002	-0.008	0.005	-0.031
Systolic blood pressure squared	0.000	-0.001	0.001	-0.005	-0.001	0.004	-0.005	0.024
Total cholesterol	-0.001	-0.004	-0.002	-0.015	0.002	0.014	0.000	0.002
Total cholesterol squared	0.001	0.005	0.001	0.007	-0.002	-0.010	0.000	-0.003
HDL cholesterol	0.000	0.000	0.001	-0.001	0.000	0.000	0.000	0.000
Haemoglobin	0.004	-0.011	-0.003	-0.002	-0.002	0.001	0.009	-0.019
Haemoglobin squared	-0.006	0.015	0.001	0.000	0.001	0.000	-0.013	0.028
Fibrinogen	0.009	-0.020	0.007	-0.013	-0.004	0.005	0.000	0.001
Fibrinogen squared	-0.008	0.018	-0.009	0.015	0.003	-0.004	0.000	0.000
Ferritin	0.001	0.000	0.001	0.003	0.000	0.000	0.000	0.000
Ferritin squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Waist:Hip ratio	0.005	-0.024	-0.008	0.147	0.002	-0.024	-0.004	0.048
Waist:Hip ratio squared	-0.006	0.026	0.008	-0.137	-0.002	0.022	0.004	-0.040
Body Mass Index								
<20	0.000	0.000	0.002	0.008	0.001	0.004	0.000	-0.001
25-30	0.000	0.000	-0.001	-0.001	0.000	0.000	-0.001	0.000
30-35	0.000	0.000	0.000	-0.002	0.000	0.000	0.000	-0.001
35-40	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
>40	0.000	0.000	0.000	-0.001	0.000	0.000	0.000	0.000
Ward-level health variables								
SMR (aged<75 years)	0.000	0.000	-0.008	0.000	-0.001	0.000	-0.002	0.000
SIR (aged<75 years)	0.005	-0.001	0.010	0.001	0.007	0.001	0.002	0.000
Sub-total	0.004	0.004	0.011	0.019	0.005	0.001	-0.003	0.013
Not working due to ill health								

Permanent long-term sickness	-0.001	0.002	-0.004	0.010	-0.001	0.002	-0.003	0.006
Retired from paid work	-0.001	0.002	-0.003	0.007	-0.001	0.001	-0.006	0.015
Temporary sickness or injury	-0.001	0.001	-0.001	0.001	0.000	0.000	-0.001	0.001
Sub-total	-0.003	0.005	-0.008	0.018	-0.002	0.003	-0.009	0.022
ln(Income)	-0.009	0.002	0.019	0.000	0.008	0.000	0.013	-0.002
Social class of head of household								
IIIN, IIIM	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
IV, V or other	-0.003	0.001	-0.001	0.000	-0.001	0.000	-0.002	0.000
Sub-total	-0.004	0.001	-0.002	0.000	-0.002	0.000	-0.003	0.000
Economic activity								
Going to school or college full time	0.001	0.001	0.001	0.002	0.001	0.003	0.001	0.004
Looking after the home	-0.002	0.003	0.004	0.001	0.000	0.000	-0.006	0.011
Waiting to take up paid work	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Looking for paid work	0.001	0.000	0.001	0.000	0.000	0.000	-0.001	0.000
Doing something else	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sub-total	0.000	0.004	0.006	0.003	0.001	0.003	-0.006	0.015
Education								
Higher education less than a degree	0.000	0.000	0.003	0.001	0.001	0.000	0.001	0.000
A level or equivalent	0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000
GCSE or CSE or equivalent	0.001	0.000	0.001	0.003	0.000	0.001	0.000	0.000
Other qualification	0.000	0.001	0.001	0.002	0.000	0.000	0.000	0.000
No qualification	-0.004	0.004	-0.004	0.003	0.002	-0.001	0.002	-0.002
Sub-total	-0.003	0.005	0.002	0.009	0.003	0.000	0.003	-0.001
Ethnic group								
Black	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
Indian	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Pakistani	-0.003	0.001	0.009	0.008	0.001	0.000	0.000	0.000
Bangladeshi	-0.003	0.001	0.012	0.007	0.001	0.000	0.005	0.002
Chinese	0.000	0.000	0.001	0.006	0.000	0.000	0.000	0.002
Other non-white ethnic group	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sub-total	-0.007	0.002	0.023	0.023	0.002	0.001	0.006	0.005
Supply variables								
Access domain score	-0.003	0.001						
Proportion of outpatients seen<26 weeks			0.001	0.001				
GPs per 1000 patients					0.000	0.000		
Average distance to acute providers							-0.001	0.000
HA effects	-0.002	0.011	-0.003	0.015	-0.001	0.013	0.002	0.007
Year effects								
1999	0.002	0.001	-0.007	-0.005	-0.003	0.001	0.000	0.000
2000	-0.001	-0.001	0.004	0.010	0.001	0.005	-0.001	-0.001
Sub-total	0.001	0.000	-0.003	0.005	-0.001	0.006	-0.001	-0.001
Item non-response variables								
Self-reported general health	-0.009	0.017	0.003	-0.003	0.001	0.000	0.002	-0.003

Limiting longstanding illness	0.012	-0.022	-0.009	0.007	0.002	-0.001	-0.002	0.004
Days cut down	-0.008	0.015	0.003	-0.002	-0.003	0.002	-0.002	0.004
Type of longstanding illness	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GHQ-12 score	-0.002	0.001	0.003	0.004	0.001	0.001	0.000	0.000
Height	0.002	-0.002	0.002	-0.001	0.001	-0.001	-0.001	0.002
Weight	-0.002	0.004	0.003	-0.002	-0.001	0.001	0.000	0.001
Systolic blood pressure	0.000	0.000	-0.001	-0.001	0.000	0.000	0.000	0.000
Total cholesterol	-0.002	0.002	-0.002	-0.005	0.000	-0.001	0.001	0.000
HDL cholesterol	0.001	-0.001	0.001	0.003	-0.001	0.002	-0.001	0.000
Ferritin	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000
Haemoglobin	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000
Fibrinogen	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Waist:Hip ratio	0.000	-0.001	0.001	0.019	0.000	0.001	0.000	0.001
Body Mass Index	0.001	-0.002	-0.003	0.002	0.001	0.000	-0.001	0.002
Ward	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Income	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Social class of head of household	-0.006	0.010	-0.002	0.002	-0.002	0.002	-0.007	0.018
Economic activity	0.012	0.005	0.001	0.002	0.004	0.009	0.001	0.001
Education	-0.002	-0.002	0.013	0.033	0.002	0.005	0.013	0.029
Ethnic group	-0.001	0.002	-0.004	0.003	-0.002	0.001	-0.003	0.006
Sub-total	-0.005	0.027	0.008	0.061	0.003	0.021	-0.001	0.064
Total	-0.067	0.243	-0.028	0.440	0.001	0.128	-0.033	0.187