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

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Abstract

Achieving equity in healthcare, in the form of equal use for equal need, is an objective of many healthcare systems. The evaluation of equity requires value judgements as well as analysis of data. Previous studies are limited in the range of health and supply variables considered but show a pro-poor distribution of general practitioner consultations and inpatient services and a pro-rich distribution of outpatient visits. We investigate inequality and inequity in the use of general practitioner consultations, outpatient visits, day cases and inpatient stays in England with a unique linked data set that combines rich information on the health of individuals and their socio-economic circumstances with information on local supply factors. The data are for the period 1998–2000, just prior to the introduction of a set of National Health Service (NHS) reforms with potential equity implications. We find inequalities in utilisation with respect to income, ethnicity, employment status and education. Low-income individuals and ethnic minorities have lower use of secondary care despite having higher use of primary care. Ward level supply factors affect utilisation and are important for investigating health care inequality. Our results show some evidence of inequity prior to the reforms and provide a baseline against which the effects of the new NHS can be assessed.

Keywords: Inequity; Inequality; Ethnicity; Health measures; Utilisation; UK

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 present new estimates of the effects of a wide range of factors on individuals' use of the NHS in England and discuss the extent to which such effects can be interpreted as evidence of inequity.

In order to investigate inequity it is essential to distinguish between *need variables* which ought to affect use of health care and *non-need variables* which ought not. There is *inequality* in use when different individuals consume different amounts of care. There is *horizontal inequity* when use is affected by non-need variables, so that individuals with the same needs consume different amounts of care. There is *vertical equity* when individuals with different levels of need consume appropriately different amounts of health care. There has been little analysis of vertical inequity in health care use because, in addition to making value judgements about which variables are needs variables,

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judgements are required about the way in which use ought to vary amongst individuals with different needs (Sutton, 2002).

In this paper, like almost all the equity literature, we restrict attention to horizontal equity. We follow the conventional view that health is a need variable but adopt a pragmatic approach to whether other variables, for example age, are indicators of need. We present our results in such a way that readers with different views on which variables ought not to affect use can form their own judgements about the existence of horizontal inequity with respect to these 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 appeared to be inequities in utilisation for some types of care, the evidence was often methodologically inadequate. In particular they pointed to the difficulties associated with defining and measuring need. Their review has been updated by Dixon, Le Grand, Henderson, Murray, and Poteliakhoff (2003) who drew particular attention to the evidence on barriers to access.

These two reviews and that by Propper (1998) draw attention to the apparent contradictory results that have emerged from "broad-brush" or "macro-level" studies, which consider all-cause (as opposed to disease-specific) utilisation. The most comprehensive analyses of health care inequalities in the UK based on individual level data and all-cause utilisation have come from the pioneering work of the ECuity project (Van Doorslaer & Wagstaff, 1998). Van Doorslaer 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 definition and measurement of need. For example, with the crudest measure of need, the distribution of GP visits was pro-poor but, with more detailed need measures, visits were unrelated to income. Income had a positive, though 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 the British Household Panel Survey from the mid-1990s show pro-poor inequity for GP consultations and strongly pro-rich inequity for specialist (outpatient) visits (Van Doorslaer, Koolman, & Puffer, 2002b; Van Doorslaer, Koolman, & Jones, 2002a).

Our data set enables us to make a number of contributions to this literature. First the data are 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, b, 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); budget allocation formulae based on new measures of need covering the bulk of NHS funds (Department of Health, 2003c; Sutton et al., 2002); the introduction of National Service Frameworks intended to reduce variations in treatment patterns (Department of Health, 2003d); broadening performance management to include access to health care (Department of Health, 1997); and, modernisation plans to reduce inequalities (Department of Health, 2002c). 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 different conclusions about the existence and extent of inequity. Our data set has a very rich set of morbidity measures, and hence we are able to allow better 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 authority or health authority (HA)) measures.

We model the determinants of health care use by multiple regression of use on a large set of morbidity, demographic, socio-economic, and supply variables. A similar approach has been taken in Newbold, Eyles, and Birch (1995) and Abasolo, Manning, and Jones (2001), though with less rich sets of variables. We investigate horizontal inequity by examining the significance and sign of variables commonly felt to be non-need variables. The non-need variables we focus on include income, education, employment status and social class. We also consider the effects of ethnicity, which have been shown previously to influence the use of various types of health care services in Britain (Smaje & Le Grand, 1997), and which is an area of policy concern in England (Department of Health, 2000b). In the next section we describe the data used for the analysis. The analytical methods are discussed in the Analysis section. The results of the regression models are presented in the Results section and the final section concludes.

Data and variables

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 2 years and over living in England. 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. The core 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 to increase the sample size to 50,977. Summary statistics are in Table 1.

England is divided into 8414 local authority wards with a mean population of 5942 residents (range 227–37,132). We were able to use the ward level data from the AREA project linked to the individuals in the HSE sample via their postcode of residence (Sutton et al., 2002; Gravelle et al., 2003).

Health care utilisation

From 1998 onwards individuals participating in the HSE have been asked about their use of four types of health care. For outpatient visits, day case treatments, and inpatient stays, use is measured as binary variables where individuals are asked whether or not they had that 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 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 a binary variable in terms of whether the respondent visited their GP or not.

Health variables

We use the wide range of health indicators available in the HSE to control comprehensively for morbidity in our models. The variables 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". Respondents are questioned about their acute ill-health, based on the number of days in the previous 2 weeks they had to cut down on the things they usually do because of illness or injury. They are also asked whether they have a longstanding illness and its type by broad disease code. We include a dummy variable indicating whether at least one of these illnesses is limiting, and we measure the extent of comorbidity by the number of longstanding illnesses.

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

Ward-level health variables: SMR (aged <75 years); SIR (aged <75 years).

The health variables in the first category are included in most of the data sets that have been used previously for measuring equity in the UK. The detailed health measures included in the second category have rarely been used and the ward-level health variables have not been used in previous studies.

Income

Our income variable is derived from the income of the whole household before deductions for income tax and national insurance. The HSE household income variable contains 31 income bands of different widths with an open-ended top band. 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. To do so we compared the number 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 computed as the value at half the cumulative density within the band.

The 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). After comparison with results using power functions of income, we used the natural logarithm of the equivalised income as the income measure, as in van Doorslaer et al. (2000).

Table 1
Sample-weighted means and standard deviations of variables included in the regression models ($n = 50,977$)

Variable	Mean	Std. dev.	Variable	Mean	Std. dev.	Variable	Mean	Std. dev.
Health service utilization			*Number of longstanding illnesses*			*Education*		
GP consultations	0.150	0.357	0	0.593	0.491	Degree	0.104	0.306
Outpatient visits	0.299	0.458	1	0.259	0.438	Higher education less than a degree	0.083	0.275
Day case treatment	0.066	0.248	2	0.100	0.300	A level or equivalent	0.083	0.276
Inpatient stays	0.086	0.281	3	0.034	0.182	GCSE or equivalent	0.180	0.385
Age and sex			4 or more	0.013	0.114	CSE or equivalent	0.042	0.201
Female	0.535	0.499	*GHQ-12 score*			Other qualification	0.040	0.195
Age (years/100)	0.403	0.234	0	0.461	0.498	No qualification	0.265	0.441
Self-reported general health			1	0.112	0.315	*Ethnic group*		
Very good	0.369	0.483	2	0.064	0.245	White	0.930	0.255
Good	0.404	0.491	3	0.041	0.199	Black Caribbean	0.009	0.095
Fair	0.169	0.375	4	0.029	0.167	Black African	0.007	0.086
Bad	0.043	0.203	5	0.021	0.142	Black Other	0.002	0.045
Very bad	0.013	0.113	6	0.016	0.126	Indian	0.015	0.123
Limiting longstanding illness	0.229	0.420	7	0.014	0.116	Pakistani	0.010	0.098
Acute ill health (days cut down)			8	0.011	0.105	Bangladeshi	0.005	0.067
0 days	0.839	0.367	9	0.010	0.098	Chinese	0.003	0.059
1–3 days	0.051	0.219	10	0.009	0.095	Other non-White ethnic group	0.015	0.122
4–6 days	0.026	0.160	11	0.008	0.087	*Supply variables*		
7–13 days	0.027	0.161	12	0.008	0.089	Access domain score	−0.302	0.681
14 days	0.055	0.228	ln(Income)	9.643	0.765	Prop. outpatients seen < 26 weeks	0.940	0.028
Ward-level health variables			*Social class of head of household*			GPs per 1000 patients	0.568	0.090
SMR (aged < 75 years)	102.22	28.348	(I) Professional	0.067	0.251	Average distance to acute providers	24.144	12.145
SIR (aged < 75 years)	100.55	31.442	(II) Managerial/technical	0.288	0.453			
						Year		
Longstanding illness			(IIIn) Skilled non-manual	0.135	0.342	1998	0.430	0.495
Neoplasms and benign growths	0.013	0.115	(IIIm) Skilled manual	0.283	0.451	1999	0.398	0.490
Endocrine and metabolic	0.045	0.207	(IV) Semi-skilled manual	0.146	0.353	2000	0.172	0.377
Mental disorders	0.026	0.160	(V) Unskilled manual	0.048	0.213	*Item non-response variables*		
Nervous system	0.034	0.181	Other	0.029	0.167	Self-reported general health	0.002	0.039
Eye complaints	0.023	0.149	*Economic activity*			Limiting longstanding illness	0.002	0.041
Ear complaints	0.024	0.154	In paid employment	0.423	0.494	Days cut down	0.002	0.042
Heart and circulatory	0.098	0.297	Going to school/college full time	0.038	0.192	Type of longstanding illness	0.000	0.018
Respiratory system	0.100	0.300	Permanent long-term sickness	0.033	0.179	GHQ-12 score	0.197	0.398
Digestive system	0.041	0.198	Retired from paid work	0.189	0.391	Ward	0.000	0.020
Genitourinary system	0.019	0.138	Looking after the home	0.090	0.286	Income	0.159	0.366
Skin complaints	0.022	0.148	Waiting to take up paid work	0.002	0.041	Social class of head of household	0.003	0.057
Musculoskeletal system	0.160	0.366	Looking for paid work	0.017	0.128	Economic activity	0.202	0.402
Infectious disease	0.002	0.041	Temporary sickness or injury	0.003	0.054	Education	0.203	0.402
Blood and related organs	0.005	0.073	Doing something else	0.004	0.061	Ethnic group	0.003	0.054
Other complaints	0.002	0.041				Proxy respondent	0.161	0.367

Socio-economic variables

We also use categorical variables describing: the social class of the head of the household (eight categories based on the Registrar General's classification); the highest educational level achieved (seven categories); economic activity (nine categories); and ethnicity (nine categories).

Supply variables

After experimenting with a variety of ward-level supply variables we selected four: the Index of Multiple Deprivation (IMD) access domain score; average proportion of outpatients seen within 26 weeks at the providers used by ward residents; average GPs per 1000 patients at the practices with which the ward residents are registered, and average distance to acute providers used. 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. The four measures were used in the GP consultation, outpatient visit, day case treatment and inpatient stay models, respectively.

We also included HA effects to control for unobserved supply factors (see Sutton et al. (2002) and Gravelle et al. (2003) 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.

Analysis

Investigating horizontal inequity

To examine horizontal inequity requires a positive model of the determinants of health service use and a set of value judgements about which factors ought to affect use and which factors ought not. Different value judgements may affect conclusions about the existence of inequity. For simplicity, suppose that the best-fitted model of individual health service use is linear in the explanatory variables:

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

where ethnicity is a dummy variable taking on the value 1 if the individual is non-white and zero otherwise and 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 and non-need variables are variables which ought not to affect use.

The equity implications of the results from an empirical model like (1) depend on value judgements about which variables are need variables and on factual judgements about whether the estimated equation suffers from omitted variable bias. We illustrate the importance of these two types of judgement in a number of examples, which by no means exhaust the possible cases.

(i) Suppose we believe that use of health care should be based solely on health status and this is captured fully by the morbidity variable in (1). Then there is horizontal inequity if, holding morbidity constant, use varies with the any of the other four variables, which by assumption are non-need variables. We would conclude, for example that there is horizontal inequity with respect to income or ethnicity if $b_3 \neq 0$ or $b_4 \neq 0$.

(ii) For some types of health care, such as cervical screening, one may feel that morbidity is not a legitimate factor affecting utilisation but gender is. Thus, one would not interpret a gender effect on use as inequity for cervical screening whereas one might for screening for colorectal cancer. The equity interpretation of a gender effect on aggregate measures of utilisation may therefore be unclear.

(iii) Suppose we have the same value judgements as in (i) but believe that the morbidity variable does not capture all aspects of morbidity and that the unobserved components of morbidity are negatively correlated with income. Then, if income has no direct effect on use the coefficient on income will reflect its negative correlation with unobserved morbidity and so ought to be negative. Hence if $b_3 = 0$ or $b_3 > 0$ there is horizontal inequity with respect to income. If $b_3 < 0$ we cannot draw any conclusion about inequity unless we make much stronger factual judgements about the strength of the correlation between income and unobserved morbidity, and about how large the effect of unobserved morbidity on use ought to be. The same argument would hold for ethnicity.

(iv) Some value judgements are more contentious than others. For example, the judgement that income ought to have no direct effect on use is less contested than the judgements about the appropriate effect of age. Williams (1997) has suggested that entitlement to health care should decline with age since capacity to benefit declines and because 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. Alternatively, 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. These latter arguments imply that use should increase with age: $b_2 > 0$.

(v) 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, Donaldson, & Gerrard, 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. Here we consider only 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 ($b_5 > 0$). Suppose that one believes 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 also 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 factors are need variables, and $b_5 > 0$ is not an indication of horizontal inequity. Alternatively, if one believes that use of health services should not be affected by access costs, then supply factors are non-need variables, and $b_5 > 0$ is evidence of horizontal inequity. The latter view 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.

Alternatively, 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 Eq. (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 in use 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.

Irrespective of their equity interpretation, the effects of supply factors on use are important for investigating 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 be 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.

Estimation

In our data set utilisation is measured as a binary variable taking the value one or zero depending on whether the individual uses health care or not. Standard models for binary variables are the linear probability model (LPM), and the non-linear logit and probit models. The LPM can yield estimates of an individual's probability of use that are less than zero or greater than one and has heteroscedastic errors (Maddala, 1983), but has more easily interpretable results. We used the link test (Tukey, 1949; Pregibon, 1980) to choose between the LPM, logit and probit specifications. The model of interest is estimated, and the linear prediction and its square are computed. The dependent variable is then regressed using the same specification (LPM, logit, probit) in a separate model against the linear prediction, the linear prediction squared and a constant term. If the model is correctly specified the squared linear prediction should have no explanatory power. The squared linear prediction term is insignificant using the LPM for the GP consultation and outpatient visit models, and the probit for the day case treatment and inpatient stay models, so we used these specifications to model the different types of use.

It is possible that, due to the sampling strategy used in the HSE, observations are independent across Primary Sampling Units (PSUs), but not within PSUs. The

implication is that if we use estimators that assume independence within these clusters the standard errors on the regression coefficients may be too small and we will overestimate the statistical significance of the independent variables in our models. We therefore controlled for clustered sampling within PSUs using Huber/White/sandwich robust variance estimators that allow for within-group dependence (Kish and Frankel, 1974).

We also use sample weights to adjust for the fact that different observations, in particular those in the boost samples, have different probabilities of selection. Unweighted estimation is more efficient than weighted estimation if the probability of selection in the sample is based on exogenous variables (Wooldridge, 2002, pp. 596–598). In the HSE the sample weights are determined by age, sex, ethnicity and PSU. While we control for age, sex and ethnicity in the models, the stratification may not be exogenous because we do not include PSU variables. Hence, we use sample weights in the analyses. Since our data set is pooled across three survey years we took the weights reported in each year and rescaled them by dividing the individual weight in each year by the mean weight in that year. To adjust for disproportionate sampling across years we then multiplied the rescaled weight by the proportion of the pooled sample in that year.

In the HSE, information about children aged 2–12 years was obtained from a parent, with the child present. We include a dummy variable for such proxy responses.

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 and we included dummy variables for each imputed item to indicate item non-response. For categorical variables, missing values were assigned to the omitted category and we added a dummy variable for item non-response. We use this approach in preference to other methods for dealing with missing data (such as hotdecking) because in our sample items may not be missing at random. 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 that is not contaminated by the imputation for non-responders.

The models were estimated using Stata version 8.2.

Results

Sample-weighted summary statistics for the variables included in the regression models are presented in Table 1. For the binary variables (health service utilisation, gender, the longstanding illnesses and the item non-response variables) the mean values are the proportions of the sample in the indicated category. For the categorical variables (self-reported general health, acute ill health, number of longstanding illnesses, GHQ-12 scores, social class, economic activity, education, ethnic group, year) the mean represents the proportion of the sample in that category. For the continuous variables (age, ward-level health variables, income, the supply variables) the summary statistics give the weighted mean value.

Fifteen per cent of the sample reported at least one GP consultation in the previous 2-week period. The figures for outpatient visits, day case treatment and inpatient stays in the previous year are 30%, 7% and 9%, respectively.

Each of the regression models for the four types of use contains over 200 variables (including the 94 HA variables and the eleven 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 2–6.

The results for each continuous variable give the marginal effects of the variable on the probability of use holding all other variables constant. For binary independent variables the marginal effect is computed as the change in the probability of use as the variable changes from zero to one. For models estimated with the LPM (GP consultation and outpatient visits) the marginal effect is simply the coefficient from the regression. For the day cases and inpatient stays probit models, the marginal effect of a variable depends on the coefficients and the levels of *all* variables. We compute and report the marginal effect for each variable from the probit models at the mean values of the other independent variables. Thus reported results on each variable are directly comparable across the different types of utilisation despite the different methods of estimation.

We also report in the tables tests of the joint significance of subsets of variables. The coefficients are significant at the 5% level when the absolute value of the t value or z score exceeds 1.9. The results of the link tests for model specification are reported in Table 2.

Age and gender variables

The results for the age and gender variables reported in Table 2 suggest that age has non-linear effects on all types of health service use and for both sexes. Fig. 1 plots the probability of each type of use against age for both sexes. The solid lines represent the relationships based on the results in Table 2. These show the conditional effect of age on use holding all other factors constant. For comparison we also estimated regressions of utilisation against age, age squared and age cubed

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

	GP consultations LPM		Outpatient visits LPM		Day case treatment probit		Inpatient stays probit	
	Marg. eff.	t	Marg. eff.	t	Marg. eff.	z	Marg. eff.	z
Constant	0.291	5.87	−0.051	−0.33				
Age and sex variables								
Age[a]	−0.062	−4.35	−0.015	−0.86	−0.046	−3.83	−0.065	−4.98
Age squared	−1.376	−8.28	−0.862	−4.15	−0.327	−2.77	−0.844	−6.80
Age cubed	2.848	7.48	1.051	2.22	0.640	2.47	1.403	5.22
Female	−1.722	−6.35	−0.307	−0.91	−0.362	−2.04	−0.636	−3.50
Female*age	0.980	6.67	−0.377	−2.05	0.456	4.28	0.763	6.77
Female*age squared	−2.261	−5.58	1.427	2.85	−1.009	−3.67	−1.805	−6.28
Female*age cubed	1.402	4.44	−1.206	−3.12	0.603	2.93	1.134	5.33
Crude self-reported health measures								
Self-reported general health[b]								
Good	0.022	5.72	0.041	7.68	0.011	3.41	0.008	2.20
Fair	0.066	9.38	0.121	13.95	0.030	6.26	0.041	7.65
Bad	0.083	5.56	0.206	13.59	0.055	6.69	0.073	7.80
Very bad	0.131	5.09	0.264	11.35	0.075	5.58	0.217	12.96
Limiting longstanding illness	0.001	0.11	0.065	6.91	0.007	1.74	0.033	6.68
Acute ill health (days cut down)[c]								
1 to 3 days	0.123	11.59						
4 to 6 days	0.222	12.76						
7 to 13 days	0.300	16.99						
14 days	0.236	19.65						
Ward-level health variables								
SMR (aged < 75 years)	−0.0002	−1.85	0.0001	0.83	0.00001	0.10	0.0001	1.44
SIR (aged < 75 years)	−0.0001	−0.69	−0.0001	−0.56	−0.0001	−1.59	−0.0001	−1.47
Tests of restrictions								
Age and sex variables = 0	$F = 25.67$, $p < 0.0001$		$F = 10.82$, $p < 0.0001$		$\chi^2 = 50.44$, $p < 0.0001$		$\chi^2 = 244.90$, $p < 0.0001$	
Self-reported general health variables = 0	$F = 26.30$, $p < 0.0001$		$F = 78.51$, $p < 0.0001$		$\chi^2 = 90.85$, $p < 0.0001$		$\chi^2 = 279.21$, $p < 0.0001$	
Acute ill health variables = 0	$F = 190.11$, $p < 0.0001$							
Ward-level health variables = 0	$F = 4.96$, $p < 0.0001$		$F = 0.35$, $p = 0.706$		$\chi^2 = 6.97$, $p = 0.031$		$\chi^2 = 3.23$, $p = 0.199$	
N	50968		50922		50927		50932	
(Pseudo-)R^2	0.1174		0.1220		0.0606		0.1163	
Link test[d]	$t = -1.04$, $p = 0.300$		$t = -1.40$, $p = 0.163$		$z = -0.073$, $p = 0.265$		$z = -0.043$, $p = 0.197$	

[a]Age/100.
[b]The baseline category is "Very good".
[c]The baseline category is zero days.
[d]The test is based on the reported significance of the prediction squared term.

separately for men and women for all four types of use. These unconditional estimated relationships between age and use are plotted as the dashed lines in Fig. 1. The estimated conditional and unconditional relationships differ because the unconditional relationship between probability of use and age picks up the effects of other variables which affect use and which are correlated with age. The most obvious example is that morbidity has a positive effect on use and older individuals have higher morbidity.

For men the effect of age on the probability of a GP visit is similar in the unconditional and conditional models, with the probability of use first declining with age and then increasing before declining again in old age. For outpatient visits, the unconditional model has the probability of use increasing with age over the entire range of ages. The conditional results have utilisation propensity declining with age up to 54 years, and increasing thereafter. For day case treatment and inpatient stays the unconditional effect is broadly the same, with the probability of use declining with age and then increasing from age 14 and 22, respectively.

For women there is more of a contrast between the conditional and the unconditional results. For GP visits,

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

	GP consultations LPM		Outpatient visits LPM		Day case treatment probit		Inpatient stays probit	
	Marg. eff.	t	Marg. eff.	t	Marg. eff.	z	Marg. eff.	z
Type of longstanding illness								
Neoplasms and benign growths	0.023	1.04	0.307	13.72	0.076	6.12	0.108	7.94
Endocrine and metabolic	0.055	4.42	0.133	9.05	0.012	1.83	0.005	0.73
Mental disorders	0.035	2.18	0.013	0.74	−0.005	−0.66	−0.005	−0.62
Nervous system	0.017	1.27	0.060	4.01	0.017	2.33	−0.004	−0.59
Eye complaints	−0.015	−1.00	0.178	9.10	0.033	3.42	0.007	0.83
Ear complaints	0.015	1.06	0.088	4.41	0.031	3.33	0.004	0.45
Heart and circulatory	0.049	5.01	0.075	6.27	0.010	1.89	0.024	3.98
Respiratory system	0.042	5.40	0.045	4.65	0.007	1.45	0.006	1.17
Digestive system	0.034	2.74	0.109	7.20	0.048	6.21	0.017	2.31
Genitourinary system	0.029	1.68	0.172	8.23	0.074	7.30	0.031	3.11
Skin complaints	0.050	3.10	0.074	3.99	0.031	3.28	−0.003	−0.37
Musculoskeletal system	0.002	0.24	0.067	6.44	0.014	2.65	−0.011	−2.16
Infectious disease	0.052	0.95	−0.007	−0.11	−0.005	−0.18	−0.008	−0.29
Blood and related organs	0.035	1.09	0.178	5.04	0.051	2.60	0.001	0.05
Other complaints	0.017	0.31	0.062	1.05	0.057	1.82	0.004	0.12
Number of longstanding illnesses[a]								
2	−0.008	−0.69	−0.031	−2.22	−0.001	−0.23	−0.003	−0.40
3	−0.019	−0.97	−0.066	−2.82	−0.023	−2.73	−0.003	−0.33
4 or more	−0.068	−2.26	−0.166	−4.60	−0.028	−2.35	−0.008	−0.51
GHQ-12 score[b]								
1	0.020	3.19	0.027	3.49	0.012	3.07	0.026	5.18
2	0.028	3.39	0.040	3.69	−0.005	−0.92	0.033	5.39
3	0.034	3.28	0.037	2.90	0.011	1.69	0.036	4.85
4	0.058	4.08	0.058	3.83	0.026	3.40	0.046	5.42
5	0.055	3.49	0.047	2.66	0.011	1.37	0.016	1.77
6	0.007	0.42	0.088	4.25	0.011	1.21	0.042	3.87
7	0.048	2.29	0.053	2.40	−0.005	−0.53	0.022	1.90
8	0.037	1.62	0.072	2.77	0.015	1.29	0.041	3.12
9	0.069	2.80	0.084	3.24	0.028	2.34	0.062	4.42
10	0.074	2.96	0.083	3.36	0.034	2.72	0.077	5.18
11	0.082	2.94	0.110	3.90	0.021	1.65	0.060	3.85
12	0.070	2.46	0.081	2.77	0.042	3.30	0.047	3.33
Test of restrictions								
Type of longstanding illness variables = 0	$F = 5.42$, $p < 0.0001$		$F = 23.65$, $p < 0.0001$		$\chi^2 = 176.14$, $p < 0.0001$		$\chi^2 = 171.61$, $p < 0.0001$	
Number of longstanding illnesses = 0	$F = 1.76$, $p = 0.153$		$F = 7.22$, $p = 0.0001$		$\chi^2 = 23.78$, $p < 0.0001$		$\chi^2 = 0.43$, $p = 0.934$	
GHQ-12 scores = 0	$F = 5.98$, $p < 0.0001$		$F = 6.90$, $p < 0.0001$		$\chi^2 = 57.04$, $p < 0.0001$		$\chi^2 = 160.21$, $p < 0.0001$	

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

the unconditional probability of use increases with age and the conditional relationship declines with age. For outpatient visits, the unconditional probability increases with age over the entire range, whereas the conditional probability declines with age up to 39 years and then increases up to age 70. The age pattern for day cases is similar for the unconditional and conditional models: the probability of use at first increases with age (up to age 46 for the unconditional model and age 22 for the conditional) and then declines (up to age 68 for the unconditional model and up to 79 for the conditional model). For inpatient stays utilisation probability increases with age up to 37 years and then declines up to 56 years before rising again in the unconditional model, while it declines up to age 62 and then increases in the conditional model.

Holding age constant, females are less likely to use all four types of care, though the effect is insignificant for outpatient visits.

Table 4
Effect of socio-economic variables and ethnicity on health service utilisation

	GP consultations LPM		Outpatient visits LPM		Day case treatment probit		Inpatient stays probit	
	Marg. eff.	t	Marg. eff.	t	Marg. eff.	z	Marg. eff.	z
ln(Income)	−0.005	−1.47	0.011	2.66	0.002	1.01	0.003	1.40
Social class of head of household[a]								
(II) Managerial/technical	−0.010	−1.38	0.008	0.79	−0.006	−1.08	0.005	0.74
(IIIn) Skilled non-manual	−0.006	−0.63	0.022	1.91	0.000	−0.08	0.008	1.18
(IIIm) Skilled manual	−0.006	−0.71	0.011	1.03	−0.004	−0.78	0.007	1.02
(IV) Semi-skilled manual	−0.003	−0.39	0.019	1.69	−0.005	−0.79	0.007	0.94
(V) Unskilled manual	−0.001	−0.10	−0.021	−1.43	−0.003	−0.36	0.015	1.57
Other	0.020	1.44	0.032	1.95	−0.005	−0.50	0.025	2.40
Economic activity[b]								
Going to school or college full time	−0.038	−3.54	−0.032	−2.36	−0.023	−3.69	−0.038	−5.58
Permanent long-term sickness	0.018	1.13	0.093	5.70	0.019	2.63	0.046	5.13
Retired from paid work	0.010	1.09	0.033	2.86	0.004	0.75	0.040	6.02
Looking after the home	0.017	2.13	−0.030	−3.27	−0.006	−1.32	0.050	8.51
Waiting to take up paid work	0.019	0.39	0.112	1.85	0.052	1.54	0.010	0.29
Looking for paid work	−0.027	−1.96	−0.020	−1.07	−0.010	−1.00	0.000	−0.04
Temporary sickness or injury	0.143	2.84	0.138	2.56	0.025	1.13	0.163	5.05
Doing something else	−0.013	−0.51	−0.013	−0.34	0.007	0.34	0.066	2.82
Education[c]								
Higher education less than a degree	0.007	0.85	0.023	1.92	0.001	0.15	0.014	2.18
A level or equivalent	0.014	1.72	0.009	0.80	−0.001	−0.22	0.005	0.83
GCSE or equivalent	0.014	2.00	0.020	2.09	0.001	0.11	0.008	1.46
CSE or equivalent	0.021	1.96	0.021	1.56	0.008	1.11	0.004	0.56
Other qualification	0.032	2.66	0.041	2.64	0.000	0.05	0.003	0.33
No qualification	0.015	1.82	−0.003	−0.31	−0.006	−1.11	0.000	0.04
Ethnic group[d]								
Black Caribbean	−0.006	−0.41	−0.011	−0.60	0.010	0.91	−0.009	−0.94
Black African	0.009	0.40	−0.007	−0.26	0.013	0.80	0.013	0.88
Black Other	0.057	1.03	0.019	0.34	0.006	0.20	−0.016	−0.74
Indian	0.030	2.25	−0.009	−0.72	−0.009	−1.17	−0.002	−0.27
Pakistani	0.022	1.43	−0.065	−4.43	−0.016	−1.87	0.004	0.39
Bangladeshi	0.029	1.16	−0.085	−3.24	0.015	0.84	−0.020	−1.08
Chinese	−0.014	−0.60	−0.122	−3.88	−0.020	−1.20	−0.039	−2.38
Other non-white ethnic group	0.012	0.78	−0.043	−2.63	−0.002	−0.16	0.014	1.14
Test of restrictions								
Social class variables = 0	$F = 1.20$, $p = 0.305$		$F = 3.17$, $p = 0.004$		$\chi^2 = 3.66$, $p = 0.722$		$\chi^2 = 10.40$, $p = 0.1089$	
Economic activity variables = 0	$F = 3.95$, $p = 0.0001$		$F = 9.76$, $p < 0.0001$		$\chi^2 = 40.11$, $p < 0.0001$		$\chi^2 = 236.04$, $p < 0.0001$	
Education variables = 0	$F = 1.64$, $p = 0.134$		$F = 3.36$, $p = 0.003$		$\chi^2 = 9.31$, $p = 0.157$		$\chi^2 = 12.02$, $p = 0.062$	
Ethnic group variables = 0	$F = 1.45$, $p = 0.169$		$F = 5.56$, $p < 0.0001$		$\chi^2 = 7.21$, $p = 0.515$		$\chi^2 = 9.62$, $p = 0.293$	

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

Crude self-reported health variables

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. For individuals with "very bad" self-reported health the probability of consulting a GP is 0.131 greater than for those with "very good" self-reported health. This is an increase of about 87% in the mean probability of use (0.131/0.150 = 0.87, where 0.131 is the coefficient from Table 2 and 0.150 is the mean probability of use in the sample). For outpatient visits, day case treatment and

Table 5
Effect of supply on health service utilisation[a]

	GP consultations LPM		Outpatient visits LPM		Day case treatment probit		Inpatient stays probit	
	Marg. eff.	t	Marg. eff.	t	Marg. eff.	z	Marg. eff.	z
Access domain score	−0.011	−2.82						
Proportion of outpatients seen < 26 weeks			0.351	2.38				
GPs per 1000 patients					0.021	1.41		
Average distance to acute providers							−0.0004	−2.44
Test of restrictions								
HA effects = 0	$F = 1.61$, $p = 0.0003$		$F = 1.41$, $p = 0.006$		$\chi^2 = 191.49$, $p < 0.0001$		$\chi^2 = 137.62$, $p = 0.002$	

[a]The models also include HA effects (not shown).

Table 6
Effect of year, item non-response and proxy response on health service utilisation

	GP consultations LPM		Outpatient visits LPM		Day case treatment probit		Inpatient stays probit	
	Marg. eff.	t	Marg. eff.	t	Marg. eff.	z	Marg. eff.	z
Year effects[a]								
1999	−0.011	−2.70	0.026	4.63	0.014	5.12	−0.0004	−0.14
2000	−0.004	−0.78	0.031	4.95	0.019	5.91	0.0002	0.05
Item non-response variables								
Self-reported general health	0.168	1.17	0.077	0.41	0.046	0.65	0.033	0.42
Limiting longstanding illness	−0.505	−2.75	−0.022	−0.11	0.017	0.24	0.047	0.50
Acute ill health	0.545	4.33						
Type of longstanding illness	0.659	4.25	0.080	0.36	0.074	0.54	−0.014	−0.13
GHQ-12 score	0.018	2.27	−0.018	−1.72	−0.003	−0.59	0.012	2.05
Ward	0.139	1.64	0.040	0.45	−0.055	−4.23	−0.061	−2.91
Income	−0.003	−0.56	−0.010	−1.52	0.004	1.12	0.000	−0.07
Social class of head of household	0.062	1.68	0.044	0.88	−0.004	−0.18	0.098	2.86
Economic activity	−0.079	−2.36	−0.049	−1.23	−0.022	−1.03	−0.021	−0.85
Education	0.033	0.96	−0.051	−1.32	−0.005	−0.21	−0.038	−1.54
Ethnic group	−0.007	−0.16	0.059	0.98	−0.013	−0.54	0.028	0.78
Proxy response	−0.030	−2.48	−0.027	−1.59	0.001	0.08	−0.015	−1.35
Test of restrictions								
Year effects = 0	$F = 3.63$, $p = 0.027$		$F = 17.59$, $p < 0.0001$		$\chi^2 = 53.00$, $p < 0.0001$		$\chi^2 = 0.04$, $p = 0.979$	
Item non-response variables = 0	$F = 13.37$, $p < 0.0001$		$F = 4.36$, $p < 0.0001$		$\chi^2 = 18.26$, p = 0.051		$\chi^2 = 79.99$, $p < 0.0001$	

[a]The baseline category is 1998.

inpatient stays the comparable percentage increases are 88% (0.264/0.299), 114% (0.075/0.066) and 252% (0.217/0.086), respectively. Having a limiting longstanding illness increases use except in the case of GP visits.

For GP consultations the number of days cut down on activities due to acute sickness in the last two weeks is highly significant and positively associated with use, although those with 14 days cut down have a lower probability of use than those with 7–13 days. We experimented with specifications including days cut down due to acute sickness for the outpatient, day case and inpatient use models. Although the variables had a significant and positive impact on use in all three models, the addition of the acute ill health variables caused the model to fail the link test for all functional forms. Since it is also arguable that a morbidity variable measured over the last 14 days is not appropriate in models of utilisation over the last 12 months, we do not report the results from these specifications for the outpatient, day-case and inpatient stay models.

Ward-level health variables

There is little evidence from Table 2 of contextual effects of ward level health measures (SMR and SIR for

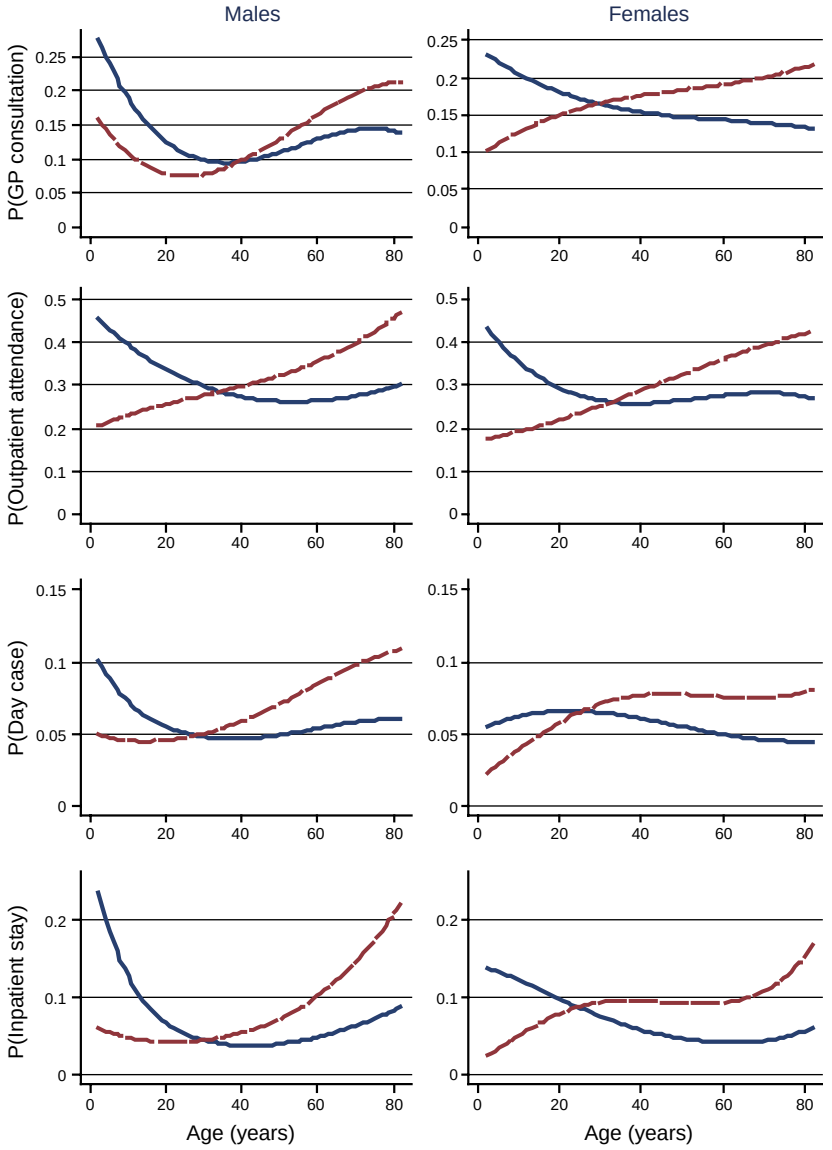

Fig. 1. Conditional and unconditional effect of age on the probability of health service utilisation. *Note*: Conditional results (solid line) were obtained from multiple regression with cubic function of age and all other variables. Unconditional results (dashed line) were obtained from regression with powers of age only.

individuals aged less than 75 years) on individual utilisation.

Detailed self-reported health measures

Table 3 shows that worse psychosocial health (captured by the GHQ-12 score) is also generally associated with more use. The 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, such as diabetes, have the largest effect on GP visits increasing the mean probability of use by 37% (0.055/0.150). Neoplasms and benign growths have the greatest effect on the probability of hospital use. For outpatient visits, day cases and inpatient stays the increase in the mean probability of use associated with these disorders is 103% (0.307/0.299), 115% (0.076/0.066) and 126% (0.108/0.086), respectively.

A comprehensive treatment of comorbidity effects would have to allow for all $2^{15}-(15+1)$ possible combinations of the longstanding illnesses. We have adopted a more parsimonious count structure that yields

the effects of having 2, 3 or at least 4 longstanding illnesses by averaging over the effects of each different combination of 2, 3, or at least 4 longstanding illnesses. For GP, outpatient and day case use the significant and negative coefficients on the number of longstanding illnesses means that individuals with comorbidity have a lower total probability of use than would be expected from addition of the marginal effects of each of the specific illnesses. A plausible explanation is that comorbidities are treated together and so do not require separate visits. The comorbidity effects are both individually and jointly insignificant in the inpatient model.

Personal characteristics

Table 4 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 are statistically significant at the 5% level. Thus there is some evidence of pro-rich inequality for all types of hospital care and of pro-poor inequality in GP visits.

Social class has few significant effects on the probability of use. The only individually significant coefficients suggest that unclassified individuals in the "Other" category have higher probability of use relative to social class I (professional) for outpatient visits and inpatient stays. The social class variables are also jointly insignificant for GP visits, day cases, and inpatient stays. Thus social class exerts little independent influence on use once account is taken of income, education, and economic activity.

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. Since we already allow for age, the retirement category is likely to be picking up those who have retired early on health grounds. The results for these three categories suggest that our rich set of morbidity variables do not capture the full effect of ill health on use or that some of these groups attend for non-health reasons, such as sickness certification. Those going to school or college full time are less likely to use all types of services. Individuals looking after the home or family are more likely to visit the GP and receive inpatient care, but are less likely to receive outpatient treatment, while those looking for paid work have lower than expected GP use.

Education has no significant association with day case or inpatient treatment. For GP consultations there is evidence that, relative to those with higher educational attainment, those with lower education attainment are more likely to visit their GP. For outpatient visits there is also evidence that differences in education have an effect on utilisation but there is no clear gradient relative to the effect of a degree.

The impact of ethnicity on health service use varies across ethnic groups and types of health care. Non-whites are generally more likely to consult GPs relative to whites, though the effect is significant only for the Indian group, who are 20% (0.030/0.150) more likely to visit the GP than the white ethnic group. Non-white groups are less likely to have an outpatient visit. For Pakistanis, Bangladeshis and Chinese for example the mean probability of a visit is reduced by about 22% (−0.065/0.299), 28% (−0.085/0.299) and 41% (−0.122/0.299), respectively. None of individual ethnic categories are significant in the day case model. There are no significant differences in the probability of an inpatient stay across ethnic groups with exception of the Chinese whose probability of use is smaller by 45% (−0.039/0.089).

Supply variables

Supply variables have plausibly signed and significant effects on utilisation (Table 5). 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, though the effect is insignificant. Hospital distance has a significant and negative effect on inpatient stays.

The 94 HA effects capture among other things unobserved supply factors not captured by the supply variables included in the models. We do not report the estimated HA effects but they are jointly significant for all four types of use.

Year effects, missing data indicators and proxy response

The year effects reported in Table 6 indicate that the probability of health care use increased over the period for outpatient visits and day case treatment. There is no significant time trend for GP consultations and inpatient stays.

The item non-response dummy variables are jointly significant in all models, though those on individual variables are generally insignificant for outpatient and day case use. For GP consultations, the dummy variables for missing health measures are generally significant. Four of the five missing morbidity items are positively associated with the probability of a GP visit. This suggests that individuals who did not report these items had higher morbidity than the modal group (no morbidity), since the effect of morbidity estimated on the individuals who did report these variables is to increase the probability of use. The coefficient on

missing income is insignificant in all models as is the ethnicity missing item coefficient. Thus missing data on income and ethnicity do not appear to be affecting their estimated effect on utilisation. Proxy response has a negative effect for three types of care, significantly so for GP consultations.

Concluding remarks

We have demonstrated systematic inequality in the use of healthcare in England with respect to income, ethnicity, employment status and education. Low-income individuals and ethnic minorities are more likely to consult their GP but less likely to receive secondary care. Economic activity impacts on health service use, with some unemployed groups having lower than expected use of services. Individuals with higher levels of formal education qualifications are generally less likely to consult their GP and have outpatient visits. Better supply conditions have a significant and positive effect on use.

As we have stressed the interpretation of our findings as evidence of inequity requires both value and factual judgements. If there are unobserved morbidity variables that are positively related to low socio-economic status, or if we believe that low socio-economic status groups justifiably visit the GP for non-health reasons, the pro-poor inequality in GP consultations is not evidence for pro-poor horizontal inequity. But with analogous assumptions in respect of outpatient visits, our findings suggest statistically significant pro-rich inequity.

Some non-white groups have higher than expected use of GP services, but lower than expected use of hospital services. The interpretation is complicated by potentially unobserved cultural differences that affect use, which may legitimately effect the use of health services. We might expect these unobserved cultural factors to have a smaller impact on use of hospital services, since doctors exert more influence over hospital utilisation than over GP utilisation. If so our results are evidence for horizontal inequity for ethnic minorities in the case of hospital services.

Our finding that the supply of health care has a positive effect on use does not indicate horizontal inequity if we believe that use ought to be greater when access costs are lower. However, if one believes that use of health services should not be affected by access costs, then supply factors ought not to influence use and our findings suggest supply based horizontal inequity.

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, 2002a, b) also find that low-income individuals have higher use of GP services and lower use of secondary care. Our results for ethnicity are also in line with earlier studies (Alexander, 1999; Benzeval and Judge, 1994, 1996; Smaje & Le Grand, 1997) in showing that non-whites tend to consult the GP 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, Chaturvedi, and Donovan (2003) 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. Unlike other studies we find no effect of social class on utilisation. We suspect that this is because we have a rich set of health and socio-economic variables so that there is no independent role for social class.

We believe that our rich and more recent data set offer a number of advantages over those used in earlier studies. We have better information on morbidity and so can argue that it is less likely that the estimated effects of other variables in our models are due to their correlation with omitted morbidity variables. We are also able to allow for the effect of supply factors on health service use and so reduce the risk of omitted variable bias from this source.

There are a number of limitations in our study. First, the utilisation measures are zero-one variables in four fairly crudely defined types of use and there is no information on intensity or quality of care provided. Second, the measures of morbidity are predominantly based on self-reported health that may be measured with errors which are correlated with use (Sutton, Carr-Hill, Gravelle, & Rice, 1999). Third, there may be reverse causality between use and morbidity (Sutton et al., 1999; Abasolo et al., 2001). These limitations also affect earlier studies.

Nevertheless, our results provide new evidence on inequality and inequity in the NHS in England at the start of the millennium. On one set of value and factual judgements, our findings are evidence for inequity in use by income, education, economic activity, and ethnic group. Since the extent of inequity varies by population group and by stages in the health care process devising policies to correct it may be no easy matter. The fact that our findings are generally supportive of earlier studies indicates that the qualitative effects of key variables have been quite stable over the 1980s and 1990s. Whether the effects of these variables increase or decrease following the current reforms is an important question for future research.

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