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Health, Capabilities and Functionings: An Empirical Analysis for the UK

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Sergio Destefanis[♥] **and Vania Sena**[♦]

Abstract

We analyse the relationship between socio-economic variables and health outcomes for adult participants in three waves of the British Household Panel Survey from 1999 to 2001. We adopt Sen's capability approach and compute a capability index ranking individuals on the basis of their ability to transform health and economic resources into health functionings. The results show that, even when controlling for access to health resources, socio-economic variables affect significantly the health functionings in the UK. This suggests the need for more equalitarian access policies to health care facilities.

Keywords: Health; Capability Approach; Production Frontier

JEL Classification: B59, I19

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1. Introduction

The health economics literature suggests that there exists a positive association between socio-economic status (usually measured by variables like income and education) and a variety of health outcomes indicators (like mortality and self-reported health status). Indeed, it has long been recognised that variations in income can explain a substantial part of the observed health differences (Shorrocks, 1975; Smith, 1999). Despite this, the precise mechanisms that create this positive relationship are less clear. A traditional explanation focuses on the access to health care and argues that, because of their financial resources, high-income individuals have access to more and/or better health facilities than their low-income counterparts (Menchik, 1993; Wilkinson, 1996; Benzeval and Judge, 2001). An alternative explanation considers the role that genetic or lifestyle factors can have in explaining the positive association between health outcomes and socio-economic status: high-income individuals may be healthier either for genetic reasons (being more proficient in transforming health resources into health outcomes) or because they have a healthier lifestyle. Being able to distinguish between these explanations is of paramount importance from the standpoint of health policy. Social arrangements (as opposite to a personal decision not to worry about health in particular) that prevent a curable illness from being treated are a particularly bad type of social injustice, calling for changes in those institutions that may (perversely) allow only rich people to have access to health-care services of a given standard (Smith, 1999).

In this paper, we try to assess the relative importance of these two hypotheses by using the capability approach developed by Sen (1985, 1987). This approach focuses on an individual's opportunities for conducting a life that can be valued. These opportunities are reflected in the capability set that is formed through a process where commodities (resources and income) are converted by personal, social, and environmental factors into potential functionings (or living conditions). Among the different capabilities, the capability of achieving health (or health capability) is central. Indeed, when given a choice, individuals tend to give priority to good health over the other capabilities. Therefore, Sen's notions of commodities, capabilities and functionings are extremely relevant within a health care context, where resources refer to both socio-economic variables (like income, education, wealth) and health resources (like number of visits to the general practitioner - GP - or days spent in hospital) giving the individual the capability of getting (and eventually enjoying) good health outcomes. The main contribution of this paper is to show how it is possible to compute an index of health capabilities that measures the proficiency by which individuals transform resources into health outcomes (or functionings) while at the same time, controlling for socio-economic arrangements that can influence the individual set of capabilities.

We compute the capability index for a sample of adult participants in three waves of the British Household Panel Survey (BHPS) for the period 1999-2001. For this purpose, we interpret both socio-economic and health resources as inputs of a production process where health functionings are the outputs. We assume that there is a maximum amount of functionings that can be produced by given resources; this can be interpreted as the functionings production frontier. Obviously, each individual differs in his capability of transforming resources into functionings. This means that individuals can hold different positions with respect to the functionings production frontier: their distance from the frontier allows us to measure (and rank) the individuals' efficiency in transforming resources into capabilities. In order to compute the capability index, it is necessary to estimate the production frontier. This can be done by adopting appropriate techniques from the field of frontier analysis (Fried *et al.*, 1993). Generally speaking, a production frontier can be estimated either by using parametric methods (based on econometric analysis) or by using non-parametric methods (based on linear programming methods). We adopt the parametric approach for several reasons. First, as we have a panel data-set, we can use econometric techniques to control for both unobservable heterogeneity and the presence of survivor bias in the estimates. Second, in an econometric set-up it is possible to test the significance of the impact of resources on health functionings allowing for non-linear and interaction effects.

The results from the empirical work can be summarised as follows: socio-economic variables affect health functionings, even controlling for the utilised amount of health resources. High-income and highly educated individuals enjoy better health functionings, the results suggesting that this depends on their more intensive use of health facilities. In contrast, individuals with low educational attainment and income are more likely to have poor health functionings. The existence of significant interaction terms between income and health resources suggests that the positive association found in the UK between income and health outcomes cannot be simply ascribed to different genetic factors or lifestyles. Finally, the distribution of the capability index has a very low standard deviation implying that the unobservable factors (ranging from genetic factors to lifestyle) hindering best performance are not widely spread among individuals.

The paper has the following structure. Section 2 shows how to model analytically the functionings production process, while Section 3 describes the main features of the BHPS data-set along with the variables used in the empirical analysis. The results are presented in Section 4, while Section 5 offers some concluding remarks.

2. The Functionings Production Function and the Capability Index

The purpose of this section is twofold: first, we show how the relationship between resources and functionings can be modelled using concepts drawn from production analysis and second, we illustrate formally how the capability index can be derived. Consider a production process where $\mathrm{y} \in \Re_+^M$ denotes the functionings and $\mathrm{x} \in \Re_+^N$ indicates the resources. For each vector of *x*, the output set has a production possibility frontier showing the maximum combination of functionings which can be produced for given resources. An example of a production possibility frontier is represented in Figure 1.

[Insert Figure 1 here]

Suppose now that we have two different individuals A and B: we assume they use the same vector of resources but the vector of functionings corresponding to the individual A, y^A, is different from the vector of functionings of the individual B, y^B. This difference means that the two individuals differ in their capability of transforming resources into functionings. Assume now that we want to rank the two individuals' capabilities. We can do this by comparing each individual vector of functionings to the standard given by the production possibility frontier. More specifically, if y^A is radially more distant from the frontier than y^B and needs to be expanded more than y^B in order to hit the frontier, then the capability of A to transform resources into functionings is lower than B. So a capability index can be defined as one minus the equiproportionate expansion of all outputs for given inputs. By construction, the index varies between 0 and 1. If it is equal to 1, then no expansion is possible and the individual is on the production frontier. Values smaller than 1 measure how much the individual can improve on his health capability, for given inputs.

To compute the capability index, it is necessary to model and compute the production frontier with respect to which the capability index is measured. As mentioned in the Introduction, we use the parametric frontier techniques developed within the economic analysis of production (Fried *et al.*, 1993) to estimate the functionings production frontier. For this purpose, it is necessary to make some assumptions on the functional form that models the relationship between resources and functionings. In doing this, it is important to recall that health functionings can be affected not only by the access to health resources, but also by both observable and unobservable factors varying from educational attainment, individual income, attitude towards health risks, lifestyle and genetic factors. So, in the specification of the functionings production set, it is necessary to control for this additional set of influences. Therefore, we assume a functionings production function of the following type:

$$HF_{it} = \alpha + \beta R_{it} + \chi Y_{it} + \gamma x_i + \delta Y_{it} R_{it} + u_i + e_{it} \qquad (2.1)$$

where i=1,…,N indexes groups and t=1,…,T indexes periods. HF_{it} represents the health functionings, R_{it} the health resources and Y_{it} personal income. The vector x_i includes variables, like sex, age, attitude towards health risks, marital status, location, education and so on, introduced to control for various, observable, individual characteristics. By including Y_{it} in (2.1) alongside with R_{it}, we can capture not only the extent to which high-income individuals may have easier access to health resources, but also whether their use of these resources is more effective. In addition, we allow for potential interactions and non-linearities in the relationship between health functionings, health resources and income. In particular, a set of interaction terms between personal income and health resources is introduced in (2.1). If these variables affect positively the probability of enjoying good health, then we can infer that high income enhances the impact of health resources on health outcomes, even once these resources have already been secured.

The residual e_{it}, representing idiosyncratic shocks to the frontier, is distributed as N[0,1], while the individual-specific term u_i is time-invariant and is distributed as $N[0, \sigma^2]$. The latter captures all those unobservable characteristics (such as genetic factors and lifestyle factors) that may influence the distribution of health functionings across the sample. The choice of controlling for unobserved individual heterogeneity through a set of random effects (as opposite to fixed effects) has been made for the following reasons. First, the random effects specification is common when using samples from large populations (Baltagi, 2001). Second, given the short length of the panel data-set, fixed effects estimators do not produce consistent estimates of the individual effects that would then used to compute the capability index (Baltagi, 2001). A further advantage of this specification is that it allows us to introduce among the regressors time-invariant individual variables, like location, sex and so on.

Once (2.1) has been estimated, the capability index can be computed from the estimated random effects as follows (Greene, 2003):

$$CI_i = \exp(-u_i^*) \tag{2.2}$$

where $u_i^* = \max(u_i) - u_i$. By construction, the index is bounded between 0 and 1. As mentioned above, the capability index reflects the proficiency with which the individual transforms income and health resources into health functionings. As we control for both health and socio-economic resources as well as for a host of individual characteristics in the production set, the inability of an individual to reach the frontier reflects the existence of unobservable factors, ranging from genetic characteristics to lifestyle factors not in the set of control variables, but still having the potential of affecting individuals' capabilities.

3. The Empirical Analysis: the Data and the Variables

The data for our empirical work have been extracted from the BHPS. This survey was started in 1991 and so far eleven waves of data have been collected. The initial sample was designed as a nationally representative sample of the population living in a private household and covered approximately 5,000 households and 10,000 adults. The sample was based on a two-stage stratified clustered design[1]. In the first stage, 250 postcode sectors were selected from the Small User Postcode Address File and stratified by region and socio-demographic data relying on the 1981 census. In the second stage, addresses were sampled from the postcode sectors using an analogous systematic procedure. Up to three households were selected to participate in the sample and all adults in the household were interviewed. The main effort in designing the following waves has been to follow all of the initial members of the panel over time. In this study, we focus only the three last waves (9, 10 and 11, related respectively to years 1999, 2000 and 2001). Each wave of data has been cleaned so to eliminate inconsistencies and reporting mistakes in the data. Finally, we have trimmed 1% of the data at both ends of the distributions to cut out eventual outliers. The final data set is a panel data made up of 25,402 observations across the three waves.

In order to specify (2.1) empirically, we draw upon the burgeoning literature showing that health outcomes (like mortality, incidence of diseases and self-reported health status) are associated with socio-economic variables (like income and wealth, among the others). Shorrocks (1975) first presented some estimate of the magnitude of the relationship between socio-economic status and health outcomes. Most subsequent studies (Menchik, 1993; Wilkinson, 1996; Benzeval and Judge, 2001) have concentrated on several measures of health outcomes (psychological and physical well-being, mortality and subjective self-assessment of health), assessing their relation with various measures of income (like current income, long-term income, individual income, family income, income change and poverty experience), while controlling at the same time for other variables (demographic characteristics, education, attitude towards health risks, living arrangements, and location). It is an established result from this literature that low income is typically associated to poor health. However,

[1] For more details on the BHPS sampling strategy, see the BHPS user manual (Taylor, 1998).

the literature does not clarify the precise channel through which this correlation is established (access to less and/or worse health facilities, genetic factors, lifestyle). A distinctive feature of our paper is that we try to shed light on this point, controlling for the utilised amount of health resources and assessing whether income impacts on quality and efficient use of these resources.

We decide to use the self-reported health status (SRHS) as a measure of the health functionings. This variable is constructed by asking each individual to assess his or her health status on a scale ranging from 1 (excellent) to 5 (very poor). The variable provides an ordinal ranking of perceived health status and should be interpreted as the perceived health status relative to the individuals' concept of the norm for their age group (Jones *et al.*, 2004). SHRS has been widely used in previous studies of the relationship between health and socio-economic status and in spite of its subjective nature, is considered to be a reliable measure of individual health conditions. It has been shown to be a good predictor of either mortality or subsequent use of medical care (see Contoyannis *et al.*, 2004, and quoted literature therein). The fact that SRHS is ordinal has a direct bearing on the estimation procedure as we have to use a random effects ordered probit estimator.

The resource vector contains both measures of socio-economic background and measures of health care utilisation. Among the socio-economic variables, we include a) the individual's educational attainment measured by the highest degree attained by the end of the sample period in descending order of attainment (EDUCn), from 1 (higher education degree) to 12 (no qualification) and b) the income measured as the 1999 (or initial-period) value of the RPI-deflated annual household income (INCOME). Consistently with the relevant literature, we expect income and education to have a positive impact on the probability of reporting good (or excellent) health. We have decided to use the personal income of an individual measured at the beginning of the sample period because contemporaneous personal income may be endogenous. It is possible that poor health affects labour market outcomes and therefore available income (Marmot *et al.*, 1991; Marmot, 1999). Hence, relying on initial-period income allows us to specify a causal link from income to health functionings, something which is not feasible with cross-section data (Benzeval and Judge, 2001). It may seem as that we are assuming a too restrictive specification for the income-health nexus. However, most epidemiology studies find that the main direction of causation runs from income to health, after controlling in different ways for health selection[2].

Among the measures of health-care resources, we include the number of inpatients days spent in hospital (either public or private) in the year before the survey (INPATIENT DAYS), the number of outpatients days in the year before the survey (OUTPATIENT DAYS) and the number of visits to the family GP (VISITS TO GP) in the year before the survey. While INPATIENT DAYS is a continuous variable, both OUTPATIENT DAYS and VISITS TO GP are categorical variables. OUTPATIENT DAYS ranges from 0 (no outpatient visit) to 4 (more than 10 outpatient visits), while VISITS TO GP starts from 1 (no GP visit) to 5 (more than 10 GP visits). In principle we expect that a higher use of health resources produces a better health status. However, a negative correlation can show up if individuals in poor health status, which use more health resources, are not precisely characterised by other control variables. Distinctive features of our estimates are (a) that we include these variables alongside with income and education, and (b) that each of them is interacted with income and education to control for potential differences in quality and use of health resources across socio-economic groups.

In addition to the resource variables, we also introduce a set of control variables that are deemed to be important in affecting the health outcomes. These are the individual's age (AGE), sex (SEX) and the number of accidents the individual had in the year before the survey (NACC). We expect a better reported health status among younger people and women. In addition, the presence of multiple accidents is obviously important in affecting the individual's health status and therefore his self-assessment. AGE is a continuous variable, while SEX is a binary variable taking the value of 1 if the respondent is male and 0 otherwise. Next, we control for the respondents' attitude to taking health risks by distinguishing between smokers and non-smokers. More specifically, we introduce the binary variable SMOKER taking

[2] See Benzeval and Judge (2001) and the literature quoted there for more information.

the value of 1 when the respondent smokes and 0 otherwise[3]. Finally, we control for geographical location by introducing the binary variable REGIOn, (n ranging from the value 1 - Inner London - to 18 - Scotland).

Table 1 reports the distribution (in percentage terms) of the respondents across all the variables used in our empirical analysis, across the three waves. Generally speaking, the distribution of SRHS shows that most respondents assess their health to be either excellent or good. This proportion increases across the three waves, suggesting a potential problem with survivor bias, as less healthy respondents drop out of the survey. Consistently, the majority of respondents had either up to two or no visit to their GP and spent up to two days as an outpatient. Interestingly, these proportions remain rather stable across the three waves. Also, the vast majority of the respondents had no accident in the previous year and only a third of the respondents smokes. As for the demographics of our sample, the mean age is around 49 years old and this value is rather stable across the waves; the sample is more or less evenly distributed between males and females. As for the educational attainment, more than a third of the respondents have either a first or a higher degree, while the rest of the respondents have either a high school qualification or no qualification at all. Average personal income is increasing over the three waves. Finally, the regional distribution of the respondents shows that most respondents are concentrated in the Southern part of the country, consistently with the distribution of the whole population across Britain. Table 1 also shows how the sample size evolves across the three waves of the BHPS, with the number of respondents varying from 8,273 in the first wave to 9,739 in the last wave. This variation in the sample size may indicate a potential attrition (or rather, survivor) bias problem in our data. For this reason, before we proceed to the estimation of the functionings production frontier, we test for the existence of the survivor bias and eventually correct the estimators accordingly. In the next section, we present the results of these tests and the resulting adjustments to the estimators, along with the estimates of the functionings production frontier and of the capability index.

[3] We have decided not to introduce additional variables controlling for the respondents' lifestyle as it is a well-known result from the epidemiology literature that only smoking habits, among the several lifestyle factors, significantly affect the relationship between socio-economic status and health outcomes (see Power et al., 1998; Contoyannis and Jones, 2002).

4. The Results

4.1 Testing and correcting for survivor bias

As mentioned above, the (negative) attrition found in each wave of our panel can be directly related to health problems, as individuals may die, suffer from serious illnesses and therefore drop from the survey. Long-term survivors who remain in the panel are likely to be healthier than average. More generally, the health and the socio-economic status of survivors may not be representative of the original population. Thus, failing to account for attrition may result in misleading estimates of the relationship between health functionings and socio-economic status. Veerbeck and Nijman (1992) provide a simple "variable addition" test for attrition. This consists in testing the significance in the original model of each of the following variables:

1) an indicator of whether the individual responds in the next wave (NEXTWAVE);

2) an indicator of whether the individual responds in all the three waves (ALLWAVES).

The intuition behind these tests is quite simple: if attrition is random, then indicators of the individual's pattern of responses are not associated with the SHRS, after controlling for its other determinants. Table 2 shows the results of the attrition bias test in the model where SHRS appear as the dependent variables and both the socio-economic variables and the control variables are included as independent variables. The test statistics show evidence of attrition bias as the t-ratios are significant. The signs of the marginal effects of both NEXTWAVE and ALLWAVES are consistent with the hypothesis that the probability of being in good or excellent health is higher both for respondents in the next wave and in all the three waves.

The attrition bias can be addressed by correcting the estimates with the so-called Inverse Probability Weights (IPWs), the inverse of the probability of an individual responding in the survey (after controlling for all those observable factors that can affect the response pattern)[4]. The purpose of this procedure is to give more weight to

[4] In presence of an attrition bias, the traditional probit estimators are not consistent. However, consistent estimators can be obtained by weighting the observed data by the so-called Inverse Probability Weights (Wooldridge, 2002a, 2002b). To compute the IPW estimator, we first estimate a probit model where the probability of response and non-response at each wave is determined by a set of observable characteristics that are not included in the original probit model (typically lagged values of

groups of individuals who have a high probability of attrition, as they are under-represented in the sample.

4.2 The functionings production function

The results from the IPW ordered probit estimator are presented in Table 3. As the estimated model is non-linear, t-ratios cannot be used to assess the statistical significance of the independent variables. To this purpose, it is necessary to carry out Likelihood Ratio (LR) tests on each variable or sub-sets of variables. The LR tests (reported in Table 4) confirm that most variables are significant. Income and health resources have a significant impact on individuals' health functionings, consistently with our expectations. In this sense, the results support the general findings in the health economics literature, according to which the main direction of causation runs from income to health. What is distinctive of our results is that income affects health status even if allowance is made for the utilised amount of health resources. Besides, although two of the three interaction terms (namely the interaction between income and outpatient days and between income and visits to the GP) are not significant[5], the interaction between income and inpatient days is highly significant, indicating that the impact of inpatient days on health status differs across income levels.

To provide an indication of the direction of the relationship between SHRS and each regressor, we have computed for each regressor the marginal effect evaluated at its mean value. Table 5 shows these marginal effects. As we can see, the probability of being in a poor health status increases with the number of inpatient and outpatient days, as individuals in poor health status use a larger amount of these resources. However, this does not apply to visits to the GP: in this case, using more health resources is positively related with the probability of being in good health. Higher income and educational attainment are accompanied by a lower probability of

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the original independent variables). Afterwards, the inverse of the fitted probabilities from this model are used to weight the observations for the ML estimation of the ordered probit model. Wooldridge (2002b) shows that the IPW estimator is $\sqrt{n}$ consistent and asymptotically normal.

[5] Different types of non-linearities have been tried: more specifically, we have introduced among the regressors the squared income and the interaction between the health resources and the education dummies. None of these variables was significant.

reporting poor health status[6]. It so appears confirmed that better-educated individuals pay more attention to health conditions and have less unhealthy jobs. More interestingly, the probability of being in good health is increasing in the interaction term between income and inpatient days, suggesting that at least a part of the health-income nexus must be ascribed to the institutional features of the UK's National Health System (NHS). In the NHS, access to inpatient days is strictly related to the referral pattern of GPs, and the incentives of the latter are to economise the referrals. No such strong incentives exist to economise the referrals for outpatient days. Therefore, wealthier individuals who may need inpatient treatment prefer to leave the NHS and use their financial resources to access the private health sector, while people in the NHS are likely to get inpatient treatment only in fairly serious cases.

To compute the capability index, we use (2.2). Table 6 shows the main descriptive statistics for the index: the mean value of the distribution is 0.6075 with a standard deviation equal to 0.0440, while the median is 0.6080. How can these results be interpreted? In Sen's terms, the capability index is an indicator of the "freedom" an individual has to achieve the combination of functionings he values. Freedom, however, must be broadly interpreted in this context: it does not only refer to the set of opportunities offered by the society to each member, but also to the individual characteristics that allow each person to enjoy the set of chosen functionings. In the health-care context, a low capability index may indicate the existence of behaviours or individual characteristics (like genetic illnesses) that prevent an individual from getting the most out of his resources. For instance, an individual with some unobservable illness that nevertheless lets him have a regular job may be unable to use his economic resources to enhance his health functionings. In this respect, the results we get are quite encouraging: the relatively high median implies that, for more than half of the individuals in our sample, the available health and economic resources are transformed into health functionings in a relatively successful way or (in other words) that our respondents are reasonably "free" to take advantage of the offered opportunities. In addition the low standard deviation indicates that most individuals in

[6] This result is consistent with the findings from Contoyannis and Jones (2004). Using the BHPS, they report that those who belong to the highest social class are significantly more likely to report excellent (or good) health, while those who are in the two lowest social classes are significantly more likely to report bad health. Equally they find that individuals with no qualification have a low probability of reporting excellent or good health.

the sample have more or less the same capability (as the average individual) to transform resources into health functionings. This means either that the unobservable factors (ranging from genetic factors to lifestyles) hindering best performance are not widely spread among individuals, or that individuals who have genetic problems may opt for a healthier lifestyle attaining a health capability closer to that of individuals without genetic illnesses.

Our results indicate that the positive relationship between health outcomes and socio-economic variables crucially depends on the fact that better off individuals can enjoy a more intensive use of health resources, presumably because health care access policies tend to favour them. While genetic factors cannot be altered, there is scope for policy-makers to introduce measures that can favourably affect the capability index. To this purpose, policies are needed that severe the positive link between income and effective use of inpatient days that has been put in evidence by the econometric results.

5. Concluding remarks

In this paper, we have suggested a way to make Sen's capability approach operational within a health-care context. For this purpose, we have computed a health capability index that measures the proficiency with which individuals transform various kinds of resources into health functionings. We have assumed that the relationship between health functionings and resources can be described as a production function describing the maximum amount of health functionings (the output) that can be produced with the existing health and socio-economic resources (the inputs). The distance of an individual from the frontier measures the capability of an individual to transform resources into functionings.

On a panel of British individuals from the BHPS from 1999 to 2001, we find that socio-economic variables matter in determining individual health functionings, even when allowance is made for access to health resources. Indeed, higher income and educational attainment imply a lower probability of being in a poor health status and higher income interacted with access to inpatient days has a positive impact on the probability of being in good health. This significant interaction term suggests that the positive association found in the UK between income and health outcomes cannot be simply ascribed to different genetic factors or lifestyles. Hence there is some scope for policy-makers to expand the individual opportunity sets by devising measures that facilitate access to health care independently of income. Furthermore, the distribution of the capability index has relatively high mean (and median) and low standard error. This implies that the available health and economic resources are transformed into health functionings in a relatively successful way in our sample, with most individuals showing more or less the same capability.

LIST OF VARIABLES

Variables	Label
Number of visits to the family GP	VISITS TO GP
Number of inpatient days in the year before the survey	INPATIENT DAYS
Number of outpatient days in the year before the survey	OUTPATIENT DAYS
Number of accidents	NACC
Personal income in initial period	INCOME
Age of the respondent	AGE
Binary variable indicating the sex of the respondent	SEX
Binary variable indicating whether the respondent smokes or not	SMOKER
REGION	
Inner London	REGIO1
Outer London	REGIO2
South East	REGIO3
South West	REGIO4
East Anglia	REGIO5
East Midlands	REGIO6
West Midlands Con.	REGIO7
West Midlands	REGIO8
Greater Manchester	REGIO9
Merseyside	REGIO10
North West	REGIO11
South Yorkshire	REGIO12
West Yorkshire	REGIO13
York and Humberside	REGIO14
Tyne and Wear	REGIO15
North of England	REGIO16
Wales	REGIO17
Scotland	REGIO18
EDUC (Highest Educational Attainment)	
Higher Degree	EDUC1
First Degree	EDUC2
Teaching Qualification	EDUC3
Other Higher Qualification	EDUC4
Nursing Qualification	EDUC5
GCE A Levels	EDUC6
GCE O Levels	EDUC7
Commercial Qualification	EDUC8
CSE Grade 2-5	EDUC9
Apprenticeship	EDUC10
Other Qualification	EDUC11
No Qualification	EDUC12

Table 1. Percentage Distribution of Respondents across Waves

Variable	Wave 9	Wave 10	Wave 11
SRHS			
Excellent	14.6%	20.8%	22.5%
Good	30.1%	44.1%	42.8%
Fair	31.8%	23.1%	22.9%
Poor	17.5%	8.9%	9.1%
Very Poor	6%	3.2%	2.7%
Number of visits to GP			
None	24.6%	22.9%	23.1%
One or two visits	33.7%	34.3%	34.4%
From 3 to 5 visits	20.2%	21.6%	20.4%
From 6 to 10 visits	10.4%	11%	11.1%
More than 10 visits	11.2%	10.2%	10.9%
Number of Outpatient Days			
None	59.1%	58.2%	58.1%
One or two days	22.5%	24.5%	24.2%
From 3 to 5 days	10.3%	9.7%	9.8%
From 6 to 10 days	4.3%	4.2%	4.1%
More than 10 days	3.8%	3.3%	3.8%
Number of Accidents			
None	89.2%	90%	90.3%
One	9.3%	8.8%	8.6%
Two	1%	0.9%	0.7%
Three	0.3%	0.2%	0.2%
Four or more	0.2%	0.1%	0.1%
Smoker			
Yes	30.4%	29%	29.1%
No	38.7%	71%	70.9%
Marital Status			
Married or Living as a couple	59.2%	59.3%	58.8%
Single	40.8%	40.7%	41.2%
Sex			
Male	53.2%	52.9%	53.9%
Female	46.8%	47.1%	46.1%
Education			
Higher Deg.	2.3%	2.5%	2.6%
First Deg.	9.1%	9.5%	9.4%
Teaching Q.	2.7%	2.6%	2.4%
Other Higher Q.	18.8%	20.8%	19.8%
Nursing Q.	1.6%	1.5%	1.4%
GCE A Levels	10.1%	10.1%	10%
GCE O Levels	16.6%	16.3%	15.7%
Commercial Q.CSE Grade 2-5	2.3%	2.1%	2.3%
Apprenticeship	2.7%	2.8%	2.7%
Other Qualification	3.0%	2.8%	3.1%
No Qualification	0.7%	0.6%	0.7%
	29.2%	27.5%	28.7%

Regions			
Inner London	2.2%	2.1%	1.6%
Outer London	3.9%	3.7%	3.1%
South East	11.7%	11.9%	9.9%
South West	6%	6.0%	4.9%
East Anglia	2.7%	2.8%	2.3%
East Midlands	5.7%	5.7%	4.6%
West Midlands Conurbation	2.4%	2.5%	2%
West Midlands	3.5%	3.5%	2.9%
Greater Manchester	2.8%	2.8%	2.3%
Merseyside	1.3%	1.3%	1.1%
North West	3%	3.1%	2.5%
South Yorkshire	1.7%	1.6%	1.4%
West Yorkshire	2.3%	2.3%	2%
York and Humberside	2.3%	2.2%	1.9%
Tyne and Wear	1.6%	1.7%	1.3%
North of England	2.6%	2.7%	2.1%
Wales	20%	19.2%	15.7%
Scotland	23.1%	23.4%	18.8%
	1.2%	1.1%	1%
Age (mean)	49	49	50
Income (mean)	12663.91	13314.02	13964.77
Number of Respondents	8273	8159	9739

Table 2. Veerbeck and Nijman Tests for Attrition

Variable	*Coefficient*	*T-ratio*
NEXTWAVE	-0.081	-4.942
ALLWAVE	-0.137	-6.165

Marginal Effects	*Probability of reporting excellent health status*	*Probability of reporting very good health status*	*Probability of reporting good health status*	*Probability of reporting poor health status*	*Probability of reporting very poor health status*
NEXTWAVE	0.0164	0.0083	-0.0093	-0.0085	-0.0069
ALLWAVE	0.0271	0.0147	-0.0152	-0.0145	-0.0121

Table 3. ML Ordered Probit Estimates with Inverse Probability Weights

Regressors	*Coefficients*	*T-ratios*
Constant	-0.250	-0.605
VISITS TO GP	0.311	11.394
INPATIENT DAYS	-1.099	-4.739
OUTPATIENT DAYS	0.312	8.991
NACC	0.083	7.009
INCOME	0.007	1.419
VISITS TO GP*INCOME	-0.002	-1.247
INPATIENT DAYS*INCOME	0.073	5.044
OUTPATIENT DAYS*INCOME	-0.002	-0.839
AGE	0.002	4.739
SEX	-0.277	-26.152
SMOKER	-1.033	-10.167
EDUC1	-0.081	-3.131
EDUC2	0.119	1.895
EDUC3	0.188	4.906
EDUC4	0.163	2.778
EDUC5	0.087	3.024
EDUC6	0.114	1.509
EDUC7	0.051	1.444
EDUC8	0.069	2.364
EDUC9	0.153	2.424
EDUC10	0.082	1.420
EDUC11	-0.049	-0.885

***Note**: Regional variables are included among the regressors, but are not reported in the table.*

Table 4. Likelihood Ratio Tests

	LR	*Critical Value*
H_o: Income is not significant.	5.8*	$\chi^2(1)=3.84$
H_o: Education variables are not jointly significant.	46.94*	$\chi^2(12)=21.3$
H_o: Interaction variables between income and medical resources are not jointly significant.	14.38*	$\chi^2(3)=7.82$
H_o: Interaction variable between income and number of visits to the GP is not significant.	1.18	$\chi^2(1)=3.84$
H_o: Interaction variable between income and number of inpatient days is not significant.	13.04*	$\chi^2(1)=3.84$
H_o: Interaction variable between income and number of outpatient days is not significant.	0.5	$\chi^2(1)=3.84$
H_o: Regional variables are not significant.	63.3*	$\chi^2(17)=27.59$

***Note**: * means the variable(s) is(are) significant at 5%.*

Table 5. Marginal Effects from the IPW Ordered Probit

Regressors	*Probability of reporting excellent heath status*	*Probability of reporting very good health status*	*Probability of reporting good health status*	*Probability of reporting poor health status*	*Probability of reporting very poor health status*
Constant	-0.0628	-0.0319	0.0357	0.0327	0.0263
VISITS TO GP	0.2216	0.1125	-0.1260	-0.1155	-0.0927
INPATIENT DAYS	-0.0629	-0.0320	0.0358	0.0328	0.0263
OUTPATIENT DAYS	-0.0167	-0.0085	0.0095	0.0087	0.0070
NACC	-0.0015	-0.0008	0.0009	0.0008	0.0006
INCOME	0.0004	0.0002	-0.0002	-0.0002	-0.0002
INPATIENT DAYS*INCOME	0.0003	0.0002	-0.0002	-0.0002	-0.0001
AGE	0.0558	0.0283	-0.0317	-0.0291	-0.0233
SEX	0.2083	0.1058	-0.1184	-0.1086	-0.0871
SMOKER	0.0160	0.0086	-0.0091	-0.0086	-0.0070
EDUC1	-0.0249	-0.0108	0.0142	0.0122	0.0093
EDUC2	-0.0401	-0.0164	0.0229	0.0191	0.0144
EDUC3	-0.0347	-0.0141	0.0198	0.0166	0.0125
EDUC4	-0.0180	-0.0085	0.0102	0.0091	0.0071
EDUC5	-0.0238	-0.0104	0.0136	0.0117	0.0089
EDUC6	-0.0104	-0.0050	0.0059	0.0053	0.0042
EDUC7	-0.0141	-0.0067	0.0081	0.0072	0.0057
EDUC8	-0.0324	-0.0134	0.0185	0.0156	0.0118
EDUC9	-0.0171	-0.0078	0.0097	0.0085	0.0066
EDUC10	0.0096	0.0052	-0.0055	-0.0051	-0.0042
EDUC11	0.0205	0.0118	-0.0115	-0.0113	-0.0095

Note*: The marginal effects have been computed only for significant variables.*

Table 6. Descriptive Statistics of the Capability Index

Mean	0.6075
Mode	0.5440
Median	0.6080
Standard Deviation	0.0440
Skewness	1.7436
Minimum	0.5083
Maximum	1.0000

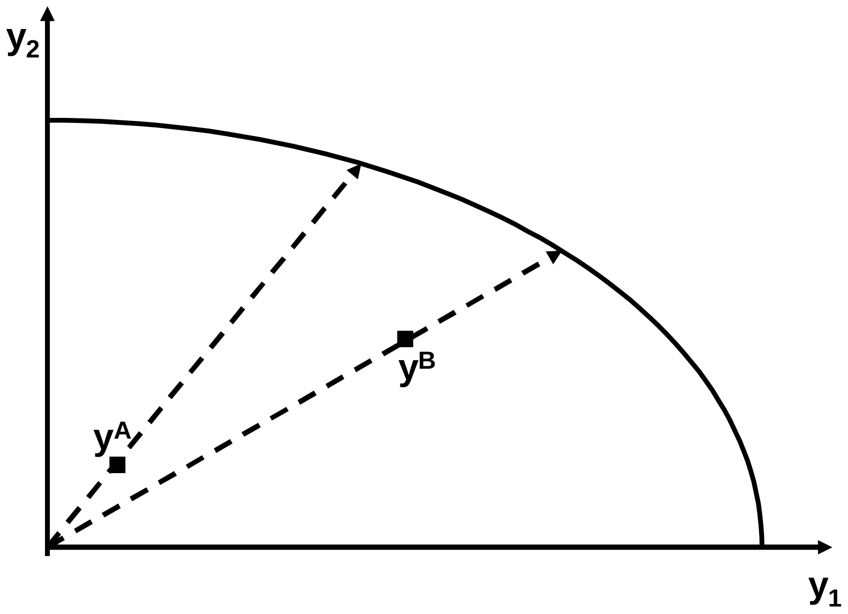

FIGURE 1

The Production Possibility Frontier

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