ESTIMATING UTILISATION OF HEALTH CARE:

A grouped data regression approach

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1. Introduction and overview

As the share of the public budget taken by health care rises, it becomes increasingly important to determine those factors influencing the demand for medical services and the decision process underlying it. However, it is well established in the health economics literature that directly applying the conventional theory of demand to health and health care leads to wrong conclusions due to the existence and nature of uncertainty and informational impactedness[1]. Hence, the usual microeconomic approach, i.e. the neoclassical framework, needs to be altered to cope with the peculiarities of the health care sector.

However, a pure demand variable appears difficult to define. First, it is of common acceptance that what the consumer really demands is health rather than health care. Thus, the demand for health care turns out to be a derived demand, although the role of health cannot be ignored if we are to get unbiased measures of other factors such as income or insurance[2] since health measures are systematically related to a number of socio-economic variables that enter the demand equations. As it has become common practice, in our model we will add one proxy variable for health status in demand equations for medical care "to control for variation in health status". Unfortunately, and despite the fact that we agree with Van der Gaag and Wolfe (1983) in that there is probably no unidimensional measure of health status that exists[3], our choice is guided by the availability of the data and therefore we will use self-assessed health as a partial measure of health status.

Moreover, not only can demand not be identified but also it is not independent of supply. Therefore, in empirical studies, health care consumption has usually been redefined in terms of **utilisation**, allowing proper acknowledgement of the influence of the supplier as well as of the role of health insurance. This approach will be adopted in this thesis. The purpose is to search, by means of econometric modelling, the main determinants of health

[1] Following McGuire et al (1988, p.151) informational impactedness means that the provider becomes instrumental in specifying the consumption pattern of the consumer
[2] Manning et al. (1981) and van der Gaag, J and Wolfe, B. (1983) take a similar view.
[3] Nevertheless, they show that a single, comprehensive health measure can be obtained to include it in health care demand analysis. Using a reduced (by the principal component analyses) set of four independent health factors with large loadings on the handicap measures, and on those of respiratory, acute and behavioural diseases, they estimate a Multiple Causes-Multiple Indicators (MIMIC) model for health care demand in which health is treated as a one-dimensional latent (unobservable) variable depending on a number of socio-economic characteristics.

care utilisation, as opposed to the demand[4] for health, in Britain using a cross section of data from the British Household Panel Survey.

We explore how alternative estimation models perform in our dataset, concluding that, rather than an ordered probit model, a grouped data regression approach turns out to be emprically more adequate. Although using a different modelling approach, our results are very much in line with those found in previous empirical work in health care demand (e.g. for the UK by Windmeijer and Santos Silva (1997)).

The thesis is structured as follows. In section 2 we review previous literature in the field consisting of, firstly the theoretical models and secondly the empirical models. Section 3 is devoted to specifying the statistical model we use. In section 4 we briefly describe the dataset and the measurement of variables employed in the empirical analysis. Section 5 presents estimation results for the alternative models tried. We end in Section 6 with some conclusions together with suggestions for further research.

2. Previous literature

2.1 Theoretical models

The survey of formal models of the demand for health and medical care presents a useful description of what modifications are necessary to extend the basic textbook model of consumer demand in order to carry out policy exercises.

A first attempt to view health as an economic good was made by Mushkin (1962), who considered health a human capital stock yielding both investment and "pure consumption" benefits. However, it does not represent a formal model of health behaviour. This was developed first by Grossman (1972) whose book stands out as the seminal work in the theory of the demand for health and medical care and provides the foundation for most of the work published afterwards. Many theoretical developments of Grossman's framework can be found, however, according to the author (1999), *with the exception of Muurinen's work* (1982), *these developments all pertain to uncertainty*. For instance, Van Doorslaer (1987) and Wagstaff (1993) fit dynamic demand for health models to longitudinal data. To Grossman, these efforts potentially are very useful because they allow, for example, one to

[4] Stoddart and Barer (1981) remark it is surprising not to find in the literature a explicit distinction between these two concepts given the evidence that health services utilisation is not compatible with the normal

relax the assumption that there are no costs of adjustment, so that lagged stock of health becomes a relevant determinant of the current stock of health. However, although consistent estimates can be obtained by using two-stages least squares with past and future values of the exogenous variables (e.g. schooling, age and income) as instruments, this implies individuals have perfect information about these future values and this may or may not be the case[5].

Earlier studies on the demand for health and medical care[6] offered useful empirical evidence on the relative effects of traditional economic variables like income or prices along with other "taste shifters" such as age, sex, health status and education. Very often, these variables proved to be important predictors of utilisation. However, health care appears as a direct argument in the standard individual utility function which ignores the basic trade-off between health and other commodities.

The household production approach offers a better insight in the trade-off involved in deciding whether to consume medical care. Here, rather than appearing directly in the utility function, medical care appears in the production function as one of the market inputs. For example, Kemna (1985) proposed a model where workers are assumed to maximise utility derived from consuming "commodities" produced in the household by combining goods bought in the market with own time investment. The objective function

$$U(H, C) \qquad (2.1.1)$$

where H is healthy time and C is the composite good, is maximised subject to the following constraints:

Budget constraint: $$Y = wH + R - p_m M \qquad (2.1.2)$$

where w is the wage rate, R denotes other non-wage income and p_m is the market price of medical care,

Health production function $$H = H(H_o, M, S, z) \qquad (2.1.3)$$

economic definition of demand.

[5] The same issue arises in estimating the rational addiction model of consumer behaviour. For a detailed discussion see Becker et al. (1994)

[6] For a survey, see Feldstein (1974) or Newhouse (1981)

where H_o is the individual predetermined health at the beginning of the period, M is medical care input, S is the level of schooling assumed to affect the efficiency of production and z denotes exposure to occupational health hazards as a consequence of an unhealthy work environment.

Market clearing wage function $w = w(z, H, S, A)$ (2.1.4)

where z are the health risks of the job, H is the individual's own health, S is the level of schooling measuring worker's human capital and A is age as a proxy for experience.

As stated above the most important breakthrough in the demand for health theory has been Grossman's (1972a,b) development of a formal framework to analyse health behaviour[7]. According to this, health can be viewed as a durable capital stock, which depreciates over time at an increasing rate but can be augmented through health investments. The decision framework then becomes intertemporal, extending to the rest of the life cycle.

To get some more insight in the basic model set up, it is useful to reproduce here the basic equations (see Grossman, 1972b or Muurinen, 1982). Each individual is assumed to maximize lifetime utility U which is a function of C_t, a composite commodity and h_t, the healthy time in period t

$$U = U\,(C_0,...,C_t;\, h_0, \ldots , h_t) \qquad (2.1.5)$$

and to inherit a stock of health capital H_0. Thereafter their stock evolves according to the relationship

$$H_t - H_{t-1} = I_{t-1} - \delta_{t-1} H_{t-1} \qquad (2.1.6)$$

where H_t is health stock at the beginning of period t, I_{t-1} is gross investment during period t-1 and δ_{t-1} is the depreciation rate in operation during the same period. In Grossman's formulation, δ_t depends only on the individual's age and is hence exogenous. The individual's income, as his utility, is an increasing function of the stock of health capital, and in selecting the optimal time path of H_t, the individual bears these benefits in mind, along with the costs of "holding" health capital. The latter comprise interest costs and any offsetting capital gains. All are increasing in the cost of new investment. Formally, the equilibrium stock of health capital is defined by the condition

$$\tau_t + a_t = \left[r + \delta_t - \tilde{\pi}_{t-1}\right]\pi_t \qquad (2.1.7)$$

where τ_t is the pecuniary marginal benefit of health capital, a_t is the non-pecuniary marginal benefit, r is the rate if interest, π_t is the marginal cost of investment and $\tilde{\pi}_{t-1}$ is its percentage change.

Grossman assumes health investment is produced by combining time and medical care equation according to a Cobb-Douglas, constant-returns-to-scale production function so that the derived marginal cost of health investment becomes a log-linear function of education.

The demand-for- health is derived by specifying functional forms for τ_t (or a_t), δ_t and π_t, and by assuming that $\left[r_t - \tilde{\pi}_{t-1}\right]$ is either zero or some function of time. To obtain the demand-for- health care equation proper, the log-linearized investment equation has to be combine with the investment production function[8] and the cost-minimization condition for gross investment. The typical form of the individual's demand function for medical services that emerges from the "pure investment"[9] version of Grossman's model (see Muurinen 1982, p.10 and Wagstaff 1986, p. 201) is given by

$$\ln Mt = \beta_0 + \ln H_t + \beta_1 \ln w_t - \beta_2 \ln P_t^m + \beta_3 t_t + \beta_4 X_{1t} - \beta_5 E_t \qquad (2.1.8)$$

The demand for medical services (M_t) is influenced by the latent variable "health status" (H_t); the wage rate (w_t), a price vector for medical services (P_t^m); a time trend (t_t); a vector of environmental variables (X_{1t})[10] and the level of education (E_t)[11]. The coefficient of

[7] A formulation of Grossman's model in a single period static framework can be found in Wagstaff, 1986b
[8] Assuming a Cobb-Douglas technology
[9] Grossman distinguishes between a "pure investment" submodel, which assumes that healthy time does not yield direct utility and the "pure consumption" in which the monetary benefits are assumed negligible.
[10] Following Cropper (1981) and Muurinen (1982a), the so-called allocative benefits of education are incorporated by introducing the concept of use-related depreciation of health. This is a function of age as well as of the use intensity, which is itself dependent on a number of environmental variables including education.

unity on the log of health capital reflects the derived demand hypothesis (services are not consumed per se but serve to maintain or improve upon a certain health status). The model is “neoclassical” in that stocks are assumed to adjust instantaneously to their new equilibrium values[12].

Wagstaff’s (1986) rigorous testing of Grossman’s (1972a) basic model certainly does not reinforce the confidence in the model as a description of decision-making about the use of medical care[13]. Alternatively, Usher (1975, p. 215) suggests “that falling ill is a random process dependent on the state of one’s health; and medical expenditure can be either a cost of being sick today or an investment in health tomorrow”. Therefore, uncertainty should be introduced in the demand models.

In order to introduce uncertainty into behavioural models, it is usual to assume certain parameters as random variables with known probability distributions. Consequently, in the consumer’s objective function utility is replaced by expected utility. Following Arrow (1963), two types of uncertainty model can be distinguished: uncertainty with respect to health status and with respect to the effectiveness of medical care. Each type of uncertainty leads to a different derived demand, that for health insurance and that for information respectively.

Grossman (1972) made some suggestion as to how uncertainty could be introduced into his model. It could be postulated that the consumer faces a probability distribution of depreciation rates. Using the state-preference approach (see Ehrich and Becker, 1972) to choice under uncertainty, he concluded, however, that results reached do not tend to alter conclusions from his deterministic framework. Generally, consumers might have an incentive to hold “excess stocks” of health in relatively desirable states in order to avoid

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[11] Several mechanisms (e.g. Suchman (1965; 1967), Rosenstock (1966); Andersen (1968) or Michael (1972)) by which schooling affects utilisation have been identified, but the relative importance of each remains a contentious issue.

[12] Wagstaff (1993) relaxes this assumption introducing a partial adjustment parameter reflecting the potential inability of individuals to do so. Following this and using data for a panel of Spanish households, López-Nicolas (1998) estimates a demand for private medical services equation given by

$$\text{Ln}\, M(t) = \alpha_1 + \alpha_2 \ln w(t) + \alpha_3 \ln P^m + \alpha_4 E + \alpha_5 X + \alpha_6 t + \ln \{1+[\tilde{H}(t) /(\delta(t) * \mu)]\}$$

where, in addition to traditional variables, some terms involving the stock of health are considered, namely, its relative change over time $\tilde{H}(t) = \dot{H}(t)/H(t)$, its rate of depreciation $\delta(t)$ and a partial adjustment μ

[13] See also Zweifel and Breyer (1997) for an important criticism of Grossman’s model.

"losses" in more unfavourable "states of the world". Grossman (1972) does not give formal derivation.

An uncertainty model in which the random losses approach is elaborated in a static framework in order to derive some predictions regarding the demand for health insurance is given by Phelps (1973, 1976). Health *H* enters the utility function together with a composite good *c*; and it is produced by medical care (*m*) and own time in fixed production coefficients. The stock of health is subject to random losses with known distribution $f(\tilde{l})$. The health equation then becomes

$$H = H_o - \tilde{l} + g(m) \qquad (2.1.9)$$

where *Ho* is the endowed level of health, $\tilde{l}$ the random amount of losses (illnesses) and *g(m)* the health product of medical care. An optimal coinsurance rate and maximum payment amount are derived from maximising expected utility over all possible states of illness subject to a budget constraint. In later work (e.g. Keeler, Newhouse and Phelps, 1977), this basic model was extended to a multi-period model in order to examine the effects of deductibles and coinsurance rates on the demand for medical care services.

In all the above-mentioned applications of the random losses approach, the probabilities of falling ill are not influenced by the individual's decisions about medical care use. This exogeneity does not seem a realistic assumption in the case of, e.g., the use of preventive medicine. Cropper (1977)[14] incorporated endogenous uncertainty in health in a lifecycle model of health investment, illustrating the way in which intertemporal decision-making and the randomness of illness can be combined in a stochastic lifecycle model. Also Phelps (1978) modified his original model to make this distribution a function of preventive inputs allowing then for endogeneity. As before, expected utility is defined as the sum of all utility states multiplied by the probability of being in the corresponding state of health. For simplicity consider two states: the sick state (with probability π) and the healthy state [probability $(1-\pi)$]

$$E(U) = \pi\,(c_1, H_1) + (1-\pi)\,(c_2, H_2) \qquad (2.1.10)$$

where c_1, H_1 and c_2, H_2 refer to the consumption of other goods and health in the healthy and the sick state respectively. The consumers' health level in period t is now determined by

$$H_t = H_o - \underset{\sim}{l} + g\,(P, m) \qquad (2.1.11)$$

with H_o endowed health, $\underset{\sim}{l}$ a stochastic variable that takes the value of zero with probability $(1-\pi)$ and the value 1 with probability π. Health production g is a function of both the uses of preventive medical care (P) and acute medical care (m).

Schooling effects are introduced by Kemna (1985) in the stochastic version of his model. He makes the probability of falling ill not only a function of the consumption of preventive medical care but also of the endowed health levels, the job hazards and the schooling level.

"A more serious weakness, however, is the common but aggressively counterfactual assumption that consumers possess full information about health production functions" (Evans, 1984, p.354). Indeed, the second type of uncertainty recognised by Arrow (1963) and leading to the issue of the patient-physician relationship as being one of (imperfect) agency is completely ignored. Pauly (1980) suggests how this could be introduced. Starting from the simple single period model with utility determined by health and other goods, he assumes the marginal health product of medical care uncertain; a random variable $\tilde{g}$ with a known (subjective) probability distribution $f(\tilde{g})$. Substituting the health production and the budget constraints into the objective function results in the following expected utility maximisation problem:

$$MaxE(U) = \int_G U(Y - pM, H_0 + \tilde{g}M)\, f(\tilde{g})\, d\tilde{g} \qquad (2.1.12)$$

where G denotes the integration interval for g.

[14] See also Hey and Patel (1983) and Ippolito (1981)

He also considers the possibility of combining the physician's advice of the effectiveness of medical care in a particular health state with the individual's own prior belief. Assuming patients behave as Bayesian decision-makers[15], the general principle is that decisions are based on a mixture of own and expert information, through which suppliers can manipulate demand. Therefore, the patient is no longer the sole actor determining the demand for medical services. This phenomenon, known as "availability effect" has been largely discussed in the literature (see e.g. Fuchs and Kramer, 1973; Coyte, 1984). Taking an extreme stance, Zweifel (1981) propose a principal agent model where it is basically the physician as the patient's agent who assesses the amount of medical services utilised, following Hippocratic goals but also maximising his own utility.

Pohlmeier and Ulrich (1994) try to combine the two extremes by treating the decision making process as one consisting of two stages in the spirit of the work by Manning et al. (1981, 1987). While at the first stage the patient decides whether to visit the physician (contact analysis), it is essentially up to the physician to determine the intensity of treatment (frequency analysis). These two stages are governed by different stochastic processes and, therefore, need to be modelled separately.

2.2. Empirical models

As reviewed above, theoretical analyses of medical care utilisation suggest two traditions: consumer theory approach (Grossman, 1972) and principal-agent set-up (Zweifel, 1981).

The first approach implies one-step econometric models such as some of those estimated by Duan et al. (1983). Using data from the Rand Health Insurance Study (HIS), they examined several alternative models including:

- Analysis of variance (**ANOVA**) and analysis of covariance (**ANOCOVA**) with untransformed expenses as the dependent variable;
- A **one-part model**, which uses a two-parameter Box-Cox (1962) transformation of expenses leading to the following linear model on the log scale

$$\log(MED_i + \$5) = x_i\beta + \varepsilon_i \quad , \quad \varepsilon_i \sim N(0,\sigma^2_\varepsilon) \qquad (2.2.1)$$

[15] An attempt to explore further this approach is made by van Doorslaer (1987)

where x_i is a given row vector of explanatory variables known to affect medical expenses (*MED*) and β is a column vector of coefficients to be estimated.

- A **two-part model**, which attempts to correct the probability with nonspenders in the one-part model by separating behaviour, first in a decision to have positive expenses, and then a decision about the level of expenses, *conditional* on being positive. More formally, the model has two equations. The first is a probit equation for the dichotomous event of having zero or positive expenses:

$$I_i = x_i\delta_1 + \eta_{1i}, \quad \eta_{1i} \sim N(0, 1) \qquad (2.2.2)$$

where *MED*>0 if $I_i \geq 0$, and *MED* = 0 otherwise. The second equation is a linear model on the log scale for positive expenses:

$$\log(MED_i \mid I_i > 0) = x_i\delta_2 + \eta_{2i}, \quad \eta_{2i} \sim N(0,\sigma^2_n) \qquad (2.2.3)$$

- A **four-part model**, which separates inpatients users from non-inpatient users in order to reflect the more pronounced skewness in the right tail in (2.2.3) for total medical expense than for ambulatory. The model contains the following four equations:

$$\Pr ob(MED_i > 0) = \Phi(x_i\gamma_1), \qquad (2.2.4)$$

$$\Pr ob(INP_i > 0 \mid MED_i > 0) = \Phi(x_i\gamma_2), \qquad (2.2.5)$$

$$\log(MED_i \mid MED_i > 0, INP_i = 0) = x_i\gamma_3 + \nu_i, \qquad (2.2.6)$$

and

$$\log(MED_i \mid INP_i > 0) = x_i\gamma_4 + \varpi_i \qquad (2.2.7)$$

where $E(\nu_i) = E(\varpi_i) = 0$.

Equations (2.2.4) and (2.2.5) separate the population into three groups: nonusers, ambulatory-only users, and inpatient users. Equations (2.2.6) and (2.2.7) model the expense of the two groups of users respectively.

In comparing the models, they find ANOVA and ANOCOVA on untransformed expenditures yield imprecise results, even for samples of over a thousand cases. Using one or two-part transformed models improve the precision of the estimates. However, both produce inconsistent results because of the large number of nonspenders and the inpatient utilisation. Hence, the four-part model is preferred as the model more accurately reflecting the distribution of medical expenses.

Another remarkable study in the tradition of Grossman's model of the demand for health and health care (1972) is by Cameron et al (1988). They explore the relationship between the demand for health care and that for health insurance, which has a certain resemblance to other studies of joint discrete/continuous models[16]. Despite the added complication of uncertainty and lack of certain key variables, the Australia Health Survey (1977-78) data allow them to obtain some interesting results. Exploiting some insights of Phelps (1976), Cameron et al (1988) develop an economic model under uncertainty, which is used as the basis for a reduced form model of health insurance choice. This is needed for structural analysis of demand for health services. Their statistical model for health care utilisation takes into account the fact that the distribution of the number of physician visits (dependent variable) can take only non-negative integer values, which means that some individuals had no physician contact during the survey period, whereas others had single or multiple visits. This calls for the application of count data models. Typically these models are applied when the distribution of the dependent variable is skewed to the left, and contains a large proportion of zeros and a long right hand tail.

The Poisson model may represent a natural starting point for estimating number of physicians (Gerdtham, 1997). Assuming a random variable y which can take only non-negative integer values, the probability that y will occur N times is (with N = 0,1,2, ...) of the following form

$$\Pr ob(y_i = N) = (e^{-\lambda}\lambda_i^N)/N! \quad \text{for } N = 0,1,...,\infty \qquad (2.2.1)$$

where y_i is the count of the number of physician visits for the *i*th individual. To incorporate exogenous variables, lambda can be made a function of the covariates:

$$\lambda_i = \exp(\sum b_j X_{ij}) \qquad (2.2.2)$$

where *b*s are the coefficients and the *X*s are the covariates (with X_1 set to 1); *j* indicates the *j*th variable and *i* is the *i*th individual. Typically, the covariates include variables such as sex, age, marital status, level of income, self-assessed health, private insurance or level of education (for a more detailed description, see section **4. Data and variable specification**). The exponential form ensures non-negativity.

[16] See, e.g., King (1980), for a model of consumer's decision to rent or purchase a home and the expenditure on either or Dubin and McFadden (1984), who modelled the jointness of electrical appliance holdings and

The Poisson model appears to be reasonable whenever the data distribution resembles a Poisson distribution. Furthermore, the Poisson distribution model is easy to interpret because it can be seen as average proportionate changes in $E(y_i \mid x_i)$ for a unit change in x_i, i.e.

$$\delta E(y_i \mid x_i) / \delta x_{ij} = \beta_j E(y_i \mid x_i)$$

However, in applied work, the Poisson model is restrictive in that it assumes that the mean is equal to the variance. If this restriction is violated, the coefficients are consistent but their standard errors are not[17]. In most empirical data there exists considerable overdispersion, which may be due to state dependence (the probability of a visit to a physician in period t might depend on whether there was a visit in the period t-1). The Poisson distribution can be viewed as the result of a process of events (physician visits) whose timing is independently exponentially distributed (Amemiya, 1985) and hence overdispersion[18] might result from the violation of this independence assumption.

In his study, Cameron et al. (1988) make use of a generalisation[19] of the Poisson model, the negative binomial model (NegBin) in which the variance/mean ratio is linear to the mean. The Negbin model has all the advantages of the Poisson model but without its constraints; i.e. it captures the discrete, censored and overdispersion properties in the data. With the Negbin distribution equation (2.2.2) becomes

$$\lambda_i = \exp(\sum b_j X_{ij}) \exp(e_i) \qquad (2.2.3)$$

where λ_i is no longer determined but is itself a random variable. Because the error e_i is unobserved, it is integrated out of the expression by specifying a gamma distribution for the error term.

Estimation by maximum likelihood for the case of Australia lead Cameron et al (1988) to conclude that health status appears to be more important in determining health care services use than health insurance choice.

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electricity consumption.

[17] See, e.g. Cameron and Trivedi (1990)

[18] Cameron and Trivedi (1986) devise formal tests for overdispersion in count data model.

[19] As suggested by McCullagh and Nelder (1983)

The dataset and models employed by Cameron and Trivedi (1986) have become a test-bed for many of the recent methodological developments in microeconometric modelling of the demand for health care. For instance, Cameron and Trivedi (1993) employ them to illustrate conditional moments tests for independence of the different count variables and Cameron and Windmeijer (1996) use them to compare a range of models of goodness of fit for count data regressions, favouring those based on deviance residuals[20].

However, neither standard Poisson nor Negbin models take account of the two-part nature of the decision making process underlying the demand for health care. This more complex view is taken by the principal agent models in the tradition of Zweifel (1981). For example, Manning et al (1987) specify a four-equation model similar to that estimated by Duan et al (1983) partitioning the sample into three groups: nonusers; users of only outpatient services and users of any inpatient services. With data from a randomised experiment, they reject the hypothesis that less favourable coverage of outpatient services increases total expenditures.

Mullahy (1986) proposes a hurdle model for count data in which the basic idea is that the data-generating process is driven by two different sets of parameters and allows for a systematic difference in the statistical process governing "the hurdle" (i.e. whether an individual had visit a physician or not) and the statistical process governing how often an individual had visited a physician given at least one visit. According to Mullahy (1986) estimates of the parameter vectors can be obtained by separate maximisation of the log-likelihood function for the binary process (zero/positive visits) and that of a truncated-at-zero model for strictly positive counts (visits). In any particular application, there are many ways of specify the binary probability model and the conditional distribution of positive counts. For example, Gerdtham (1997) in testing the hypothesis of no horizontal inequity in delivery of health care with this type of model and Swedish micro data, he specifies a logit model for the probability that an individual will visit a physician and a truncated-at-zero Negbin to model the number of physician visits defined over the sample of individuals with positive visits.

The problems found when applying count data hurdle models have been pointed out by Pohlmeier and Ulrich (1994). The first relates to the problem of left censoring in duration

[20] For some other applications of count data models to health care utilisation, see Jones (1998), p.45

models. The hurdle assumes that the first visit in a give year is the contact decision, whereas subsequent visits involve the frequency decision. With no additional information, the first count in a period may be misclassified, if it belongs to an illness episode of the preceding year. The second and more serious problem is due to multiple spells. The relatively long (one year) observation period leads to a growing probability of observing multiple illness spells and multiple first contacts. Hence they extend the hurdle specification by Mullahy (1986) by using a NegBin 1 specification for both stages. Based on a cross section of the West German Socieconomic Panel they demonstrate that ignoring the two stages of the decision-making process leads to serious misinterpretation.

As an alternative to count data models, Cameron and Trivedi (1986) propose regarding the observed variable of count form as reflecting a methodological limitation in collecting data, and being just a proxy, measured on a crude ordinal scale, for the true unobserved variable which the model is intended to predict. In our case we are interested in the utilisation of medical services but not in the number of visits *per se*. Therefore, it might appear more appropriate to extend the dichotomous probit model and use the ordinal probit model developed by McKelvey and Zavoina (1975)[21]. Applied, as stated above, to a dataset derived from the Australian Health Survey 1977-8, they conclude the inferences regarding the qualitative influence of sex, income, health insurance status, health status and chronic conditions on the number of consultations would be almost the same as those based on count data model.

More recently, Deb and Trivedi (1997;1999) have questioned the appropriateness of the distinction between “users” and “nonusers” of medical care underlying the two-part or hurdle models for fixed-interval data. Because medical care can take the form of health maintenance and precautionary care (Grossman, 1972), it might be then more adequate to distinguish between groups with high and low average demand, “frequent” and “infrequent” users respectively. Using a sample from the 1987 National Medical Expenditure Survey, Deb and Trivedi (1997) estimate three variants of the negative binomial count-regression: standard, hurdle and finite mixture. With the exception of the hospitalisation outcome, their results support a two-point finite mixture model, allowing a categorisation of individuals as ill and healthy. In addition, they emphasise the importance of health status and insurance as

[21] See under **3. Statistical model and estimation methods** for an exposition.

determinants of health care demand, and the relative unimportance of income. As previously, with the RAND HIE data, they (1999) find strong evidence favouring a finite mixture variant of the latent class model.

3. – Statistical model and estimation methods

The statistical model for health care utilisation should take account of a special feature of the BHPS data – medical use is recorded as a categorical variable with 5 response categories which represents the number of consultations 1 = 0, 2 = 1 to 2, 3 = 3 to 6, 4 = 6 to 10, 5 = >10-. An appropriate specification for similarly recoded responses where the categories represent choices is the multinomial probit or logit model. However, the application of such models here would fail to account for the ordinal nature of the dependent variable. According to Greene (2000), ordinary regression analysis would err in the opposite direction, however. That is, linear regression would treat the difference between two adjacent response codes as the same, irrespective of where they lie in the distribution of responses, whereas in the fact they are only a ranking.

The most common way[22] to deal with ordered response data[23] is to use an ordered qualitative response model, usually either the ordered probit model or the ordered logit model [24]. The key feature of ordered qualitative response models is that all the choices depend on a single index function[25]

$$y_i = \beta' x_i + u_i \quad (i = 1,2,\ldots,n) \tag{3.1}$$

[22] Examples of the use of ordered probit in the health care arena include Kenkel (1995), who has categorical measures of self-reported health status and of activity limitation from the Health Promotion/Disease Prevention module of the 1985 U.S. National Health Interview Survey, and Kerkhofs and Lindeboom (1995), who, with data on heads of household aged 43-63 from the first wave of the Dutch panel survey (CERRA-I), estimated an ordered probit model for self-reported health and found evidence of state-dependent reporting bias. Also the results suggest that education influences the way in which people report their health.

[23] The ordered response model was first considered by Aitchitson and Silvey (1957) and Ashford (1959), who used the cumulative normal for the distribution function *F* in the model (then, a probit specification) and gave a maximum-likelihood analysis. Gurland et al. (1960) discussed more general functional forms for *F* in the model, including the logistic (ordered logit), and also gave the analysis by weighted least squares. Cox (1970, Chapter 7) discussed the case in which *F* has the logistic distribution.

[24] Alternative approaches are discussed by McCullagh (1980), Agresti (1984) and Rahiala and Terasvirta (1988).

[25] This makes sense when the responses have a natural ordering but does not make sense otherwise.

where y_i is the underlying response variable (number of visits to GP), x_i is a set of explanatory variables (including socio-economic and health status measures) and u_i is the residual error.

The variable of theoretical interest y_i^* (use of medical services) is unobservable but we know which of the M categories it belongs to. We observe

$$
\begin{aligned}
y_i &= 0 \text{ if } y_i^* \leq \mu_1 \\
&= 1 \text{ if } \mu_1 < y_i^* \leq \mu_2 \\
&= 2 \text{ if } \mu_1 < y_i^* \leq \mu_2 \qquad (3.2) \\
&\vdots \\
&= M \text{ if } \mu_{M-1} \leq y_i^*,
\end{aligned}
$$

which is a form of censoring.

$\mu_0, \mu_1, ... \mu_M$ denote $M+1$ real numbers (thresholds), with $\mu_0 = -\infty, \mu_{\boldsymbol{M}} = +\infty$ and $\mu_0 \leq \mu_1 \leq ... \leq \mu_{\boldsymbol{M}}$, determining what value of y_i a given value of y_i^* will map into

$$y_i \in R_k \Leftrightarrow \mu_{k-1} < y_i^* < \mu_k \quad \text{for } 1 \leq k \leq M . \qquad (3.3)$$

The μ's are unknown parameters to be estimated with **β**.

The probability that an observation falls in one of the categories is given by

$$
\begin{aligned}
&\Pr ob(y_i = M) = F(\beta' x_i) \\
&\Pr ob(y_i = M-1) = F(\beta' x_i + \mu_1) - F(\beta' x_i) \qquad (3.4) \\
&\Pr ob(y_i = M-2) = F(\beta' x_i + \mu_1 + \mu_2) - F(\beta' x_i + \mu_1)
\end{aligned}
$$

and so forth.

These equations imply

$$
\begin{aligned}
&\Pr ob(y_i = M) = F(\beta' x_i) \\
&\Pr ob(y_i = M) + P(y_i = M-1) = F(\beta' x_i + \mu_1) \\
&\Pr ob(y_i = M) + \Pr ob(y_i = M-1) + \Pr ob(y_i = M-2) = F(\beta' x_i + \mu_1 + \mu_2) \qquad (3.5) \\
&\vdots \\
&\Pr ob(y_i = M) + \Pr ob(y_i = M-1) + ... + \Pr ob(y_i = 2) = F(\beta' x_i + \mu_1 + ... + \mu_{M-2})
\end{aligned}
$$

and

$\Pr ob(y_i = 1) = 1 - F(\beta' x_i + \mu_1 + \mu_2 ... + \mu_{m-2})$

where $\mu_1, \mu_2, ...\mu_{M-2} > 0$[26].

For the distribution function *F*, we can use the logistic or cumulative normal[27] defining the model as ordered logit or probit respectively.

Since y_i is treated as ordinal (categorical) it can be represented as a series of ordinal (dummy) variables by defining

$$y_{ik} = \begin{Bmatrix} 1 \text{ if } y_i \in R_k \\ 0 \text{ otherwise} \end{Bmatrix} \tag{3.6}$$

where $i = 1,..., N; k = 1,..., M$.

Assuming that the error term is normally distributed (thus, an ordered probit model) and imposing the identifying restrictions $\mu_1 = 0, \sigma = 1$[28], the probability of observing a particular value of y is

$$\Pr(y_{ik} = 1) = \Phi[\mu_k - x_i\beta] - \Phi[\mu_{k-1} - x_i\beta] \tag{3.7}$$

where Φ is the cumulative standard normal. The likelihood function for the model is

$$L = \prod_{i=1}^{N}\prod_{k=1}^{M}\left[\Phi\left(\mu_k - \beta' x_i\right) - \Phi\left(\mu_{k-1} - \beta' x_i\right)\right]^{Y_{ik}} \tag{3.8}$$

and, with independent observations, the log-likelihood takes the form

$$L^* = \log L = \sum_{i=1}^{N}\sum_{k=1}^{M} Y_{ik} \log\left[\Phi\left(\mu_k - \beta' x_i\right) - \Phi\left(\mu_{k-1} - \beta' x_i\right)\right] \tag{3.9}$$

---

[26] In actual practice we do not impose this condition that $\mu_1, \mu_2, ...\mu_{m-1}$ must be positive. The maximum-likelihood estimates usually will yield positive estimates for these parameters. If not, then one can assume that there is some specification error in the model.

[27] According to Maddala (1983, p.46), an obvious generalisation of the model is to make both thresholds different functions of x, so that $P_3 = F(\beta_1' x)$ and $P_2 = F(\beta_2' x + c) - F(\beta_1' x)$

[28] Because Y is observed only ordinally, we use the normalisation rule as in a simple probit model.

For the maximization of the log.likelihood, McKelvey and Zavoina (1975) reported good results for the convergence of the Newton-Raphson method[29]. This evaluates the matrix of second partial derivatives of L^* at the final parameter estimates, $\hat{\theta}$. This matrix, with the sign reversed, is the information matrix, whose inverse gives the estimates (asymptotic) variances and covariances of the different parameters. These can be used to perform any desired tests of significance, e.g. likelihood tests for the significance of a subset of parameters.

Marginal effects of changes in the covariates on the cell probabilities $\frac{\partial P(y=j)}{\partial x}$ are not the coefficients but these multiplied by the change in the probability distribution

$$\left[\phi(\mu_{j-1} - x\beta) - \phi(\mu_j - x\beta)\right]\beta . \tag{3.10}$$

Note that the partial effects may have the opposite signs to the estimated coefficients of the index function $x\beta$.. Moreover, in the general case, from the knowledge of the coefficients, one can only infer the marginal effects for the first and the last categories, Prob (y = 0) and Prob (y = J). What happens in the middle depends on the two densities. According to Greene (2000), one must be very careful in interpreting the coefficients of this model. Indeed, without a fair amount of extra calculations, it is quite unclear how the coefficients in the ordered probit should be interpreted[30].

Furthermore, when, as it is the case, the ranges of the underlying variable to which each category refers are known, a variant of the ordered probit, the so-called grouped data regression, appears more adequate. Theoretically, this approach is more efficient than an alternative ordered probit approach since the estimation procedure[31] utilises information on

[29] They used the ordinal-level probit model to analyse the determinants of congressional voting on the 1965 Medicare bill and reported the convergence taking between four and ten iterations, depending on the number of parameters to be estimated. Moreover, we are sure this procedure converges to the global maximum of the likelihood function since, as shown by Pratt (1981), the matrix of second derivatives of L* is everywhere negative definite. Maddala (1983) also found that the procedure converged to the same value with different initial values.

[30] This point seems uniformly to be overlooked in the received literature. Authors routinely report coefficients and *t* ratios, occasionally with some comments about significant effects, but rarely suggest upon what or in what direction those effects are exerted.

[31] A discussion of methods for estimating parameters is provided by Stewart (1983). In this thesis, the maximum likelihood approach will be adopted.

the scale of Y^* (provided by the thresholds values) to produce an estimate of σ, rather than requiring that this be normalised to one (Horowitz, 1994). With data from the British General Household Survey for 1978-1990, Sutton and Godfrey (1995) use this alternative to the ordered probit to estimate a model in which socio-economic characteristics, along with health-related attitudes and behaviour predict levels of drinking.

In this thesis we examine how these two alternative models, ordered probit and grouped data regression perform on our data[32]. For completeness, we also estimate ordinary least squares and ordered logit models[33].

We test linear and logarithmic functional forms. Following Sutton and Godfrey (1995), for the ordered response models, logarithmic forms are generated by using logged values of the threshold terms and taking logs of the continuous regressors. In the linear case, a general model was initially attempted, which included all the categories for the relevant variables in the survey. A more parsimonious model was sought by removing categories not significant at the 5% level.

In comparing the models we use a RESET test[34] as a general check for the validity of the estimated coefficients. Although there are alternative tests for misspecification of limited dependent variable model[35] (e.g. non-normality, heteroskedasticity, omitted variables and endogenous regressors), leading to inconsistency of maximum likelihood estimators, the evidence provided by Horowitz (1994) and others suggest the RESET is a fairly reliable and convenient general check. Further, recent work[36] has indicated that using only the squared term provides an effective check. Thus we use this approach at the 1% level to discriminate between models.

For those models not passing the RESET test, thus apparently misspecified, we further test for heteroskedasticity in the errors. In the case of ordinary least-squares models we employ the general test suggested by Cook and Weisberg (1983) which models the residual (e_i) variance as a function (exp) of the powers of the fitted values from the

[32] Likelihood functions are comparable since they are both discrete.
[33] To Greene (2000, p.876), "*The model can also be estimated with a logistically distributed disturbance. This trivial modification of the formulation appears to make virtually no difference in practice*". This is because the cumulative normal and the logistic distributions are very close to each other except for the tails.
[34] Ramsey (1969)
[35] See, e.g. Maddala (1995), Pagan and Vella (1989) and Glewwe (1997). See also Vuong (1989) for a more general discussion on likelihood ratio tests for model selection.
[36] Godfrey et al. (1988)

regression of the dependent variable y_i on a vector of explanatory variables z_i ($\hat{y}_i^m$) and a time trend (*t*)

$$Var(e_i) = \sigma^2 \exp(z_i t) = \sigma^2 \exp(\hat{y}_i^m t)$$

and then tests t = 0 forming the score *S* equal to the sum of squared residuals from the regression $\hat{e}_i^2 = a + z_i t + \upsilon_i$, where $\hat{e}_i^2$ is the squared of the standarized residuals[37], divided by two. Under the null hypothesis of constant variance, *S* has the χ^2 distribution with *m* degrees of freedom where *m* is the number of columns of z.

For the ordered qualitative response models we use a RESET-type test. that Assuming the heteroskedasticity is a function of an individual's age we generate weights as the product of age by the fitted values. Then, we include these weights in our model to derive the likelihood-ratio[38]

$$2(l_{UR} - l_R)$$

where l_{UR} and l_R are the log-likelihood functions evaluated at the unrestricted and restricted (weight = 0) estimates, respectively.

Under the null hypothesis of homoskedastic errors this test statistic has the χ^2 distribution with one degree of freedom (χ_1^2)[39].

Further, for the preferred model we split our sample by gender to test for heterogeneity: men and women are likely to have quite different behaviours regarding utilisation of health care.

4. – Data and variable specification

<u>4.1. The dataset</u>

The data source is the first wave of the British Household Panel Survey (BHPS) conducted between 1st September and 30th April 1991.The initial selection of households for inclusion was performed using a two-stage stratified systematic sampling procedure

---

[37] The standarized residuals are defined as $\hat{e}_i = e_i /(s\sqrt{1-h_i})$ where *s* is the root mean square error of the regression and h_i is leverage defined as $h_i = x_i (X'X)^{-1} x_i'$.

[38] See Greene (2000,Chapter 19, p. 825) for further details on testing hypothesis in models with discrete dependent variables.

[39] Since number of restrictions imposed is just one (weight = 0).

designed to give each address an approximately equal probability of selection. This longitudinal (panel) survey of private households in Great Britain (England, Wales and Scotland) is funded by the Economic and Social Research Council (ESRC) and conducted by the Institute for Social and Economic Research (ISER)[40] at the University of Essex. The main objective of the BHPS is "… *to further our understanding of social and economic change at the individual and household level in Britain*" (BHPS user manual, volume A).

The BHPS was designed as an annual survey of each adult (+ 16) member of a nationally representative sample of around 5,500 households, making a total 13,840 individual interviews in the first wave. Although measures have been taken in an attempt to maintain the sample broadly representative of the population of Britain as it changes through the 1990s, for example, if individuals split-off from original households, all adult members of their new households will be also interviewed, only using the first wave (1991) data can guarantee the sample is truly nationally representative.

The survey consists of a short household-level questionnaire and a more detailed individual (self-completion) questionnaire, which included questions "*subjective or attitudinal […] particularly vulnerable to the influence of other people's presence […] or potentially sensitive questions requiring additional privacy*"[41]. The main topics include household organisation, labour market participation, education and training, income and wealth, housing and residential mobility, health and use of health services, plus opinion-type questions exploring the socio-economic values of respondents. The questionnaire also includes additional topics, to reflect changing policy and research issues.

The initial sample for Wave One of the BHPS consisted of 8167 issued addresses drawn from a Postcode Address File. Interviews were attempted at all private households found at these addresses (subject to selection where multiple households were found). All individuals enumerated in respondent households became part of the longitudinal sample. All these sample members are known as Original Sample Members. There was at least one interview in 74% of eligible households, with full interviews with all eligible members in 65% of households. 92% of eligible individuals (households with at least one interview) responded with a full interview, with 2% of eligible individuals refusing to participate.

[40] The ISER also incorporates de ESRC Research Centre on Micro-social change, which was established in 1989 to monitor and measure social change within British households.

[41] See BHPS User's Manual, Vol.A, Section II.3. Survey Instruments

For the ease of estimation, we use a subset of the Original Sample Members who completed the questionnaire giving valid responses for the variables we use in our estimation. After excluding individuals with missing values[42] on variables of interest we obtain a working sample of 7881 individuals, consisting in 4080 males and 3801 females.

4.2. Measurement of Variables

Table 1 contains definitions of dependent and independent variables.

The dependent variable is the frequency of physician visits. Individuals in the survey were asked to approximately state the number of times they had talked to or visited a General Practitioner or family doctor about their own health during the year before the interview. The question specifically asks respondents to exclude any visits to a hospital. Responses are coded one to five depending on the interval the number of visits falls into: 1 if none; 2 if one or two; 3 if visits were between three and five; 4 if between six and ten and 5 if more than ten. The nature of the variable dictates the modelling approach to empirical estimation described in section 5.

Table 1: Definition of variables (No. Observations 7881)

Name	Definition
A. Dependent variable	
NVISIT	Number of visits to a general practitioner since 1990. Ordered categorical variable: None=1; one or two=2; three to five=3; six to ten=4, more than ten=5
B. Explanatory variables	
Socio-economic	
SEX	Two dummies (MALE and FEMALE) for males and females. Reference category are females
AGE	Age of respondents
MARITAL	Marital status. Four dummies variables for different marital status: CHILD<16=1 if children under16 years old; NVRMAR=1 if never married; MARRIED=1 if married or living as a couple and DIVSEPWID=1 if widowed, divorced or separated. Reference category is never married.
ORIGIN	Three dummies for country of origin: England (ENGL), Scotland (SCOT) or Wales (WALES)

[42] In order to allow for valid inferences where the individual is the unit of analysis, as it is in this thesis, non-response weights derived in order to adjust for this within-household non-response (for a description of the model, see User's Manual, Vol. A for an introductory discussion on weighting adjustment for sample surveys) should be considered. However, given the relatively small number of cases and since the main aim of the study is discriminating between approaches to modelling health care utilisation, we ignore this adjustment.

ETHNIC	Four dummies for ethnic group membership: white/european (WHITE); black caribbean, african or other (BLACK); indian, pakistani or bangladeshi (INDIAN) or other ethnic groups (OTHER). Reference category is white/european
QUALIF	Three dummies for highest educational qualification: Higher (HDEGREE), other qualification (OTHQUAL) or no qualification at all (NOQUAL). Ref. Category is individuals with qualification other than higher.
JSTAT	Four dummies for current labour force status: Self employed (JOBST1), in-paid employed (JOBST2); unemployed (JOBST3) and other (JOBST4). Ref. category is unemployed
JOBFT	=1 if individual works fulltime, 0 otherwise
EHHINC	Sum of total equivalent household income in the month before the interview.
NCHILD	Four dummies for dependent children aged 1 to 2 (CHILD2); 3 to 4 (CHILD4); 5 to 11 (CHILD511) and 12 to 18 (CHILD1218). Reference is households with children under 2 years
Health Status	
SAH	Three dummies (SAHEX; SAHGOOD, SAHPOOR) for excellent, good and fair or worse self-assessed health. Reference category is individuals reporting good health.
GHQ1	Score for the General Health Questionnaire. High score indicates bad health)[43].
HLZEST	Two dummies for energy compared with people of same age: more/same (ZESTSMORE) and less (ZESTLESS). Reference category is ZESTMORE.
SMOKER	Two dummies (SMOKES; NO SMOKES) for smokers or not. Ref. Category is non-smokers.
HLPRB	Two dummies (HLPRB0 and HLPROB) for absence or presence of chronic conditions/illnesses (e.g. diabetes or epilepsy). Reference category are individuals reporting no health problems.
HLLTW	Two dummies (LIMWORK; NOLIMW) for whether health limits type/amount of work or not
HLLTDA	Two dummies (LIMDAY; NOLIMDAY) for whether health limits daily activities or not
HOSP	Two dummies (HOSPYES; HOSPNO) for hospital inpatients since 1/9/90 o not. Ref. category is no hospital inpatients during the year before the interview.

As it is common use, the explanatory variables are categorised according to whether they reflect socio-economic or health status (need) factors. Following Windmeijer and Santos Silva (1997), no price variables are directly included in the model, since every individual in the UK, even those who have taken out a private insurance, is covered by the National Health Service (NHS), which is paid by payroll National Insurance (unavoidable)

[43] See Cox, B.D et al. (1987)

contributions. Further, information on private insurance taken is not available in the dataset[44].

***Socio-economic factors**

Following Pohlmeier and Ulrich (1994), I include monthly household income deflated to per person level (EHHINC). This standardisation is derived by using the household equivalence scale before housing costs contained in the survey[45]. Rather than capturing income effect, this variable is likely to reflect opportunity costs (for example, in terms of foregone time costs). The argument is that the high degree of coverage of health care services and the weak link between costs of services and the individual's payments to the National Health Service result in cost booming incentive effects, since both physician and patient have the incentive to supply and demand the maximum amount of service.

I further use three dummies for current labour force status: self-employed (JOBST1); in-paid employed (JOBST2) or other, such as on maternity leave or long term-sick or disabled (JOBST4). Reference category is the unemployed. A dummy accounting for employment status (JOBFT=1 if currently working full-time, zero otherwise) is also included. According to Phelps et al (1974) and Cauley (1987) the argument is that individuals who are employed may incur a larger "time price" of going to the physician than the unemployed. Moreover the two dummy variables separating out the employed control for potential differences in "time price" for individuals who are self-employed and those in-paid employment. Following Gerdtham (1997) I include a 0-1 dummy for individuals working full-time (JOBFT=1 if individual works fulltime, zero otherwise). This variable is defined for both self and in-paid employed people and, again, it will also reflect different time costs for people employed full-time and those who are not so.

I also include covariates on education specified as 0-1 dummy variables for individuals with higher qualification (HDEGREE)[46] and no qualification (NOQUAL). The

[44] Nevertheless, it seems likely the non-availability of this information leads to only minor misspecification, given that private insurance offer more choice at specialist level but less so at the GP (see Besley et al. 1996)
[45] According to the BHPS User's manual, this scale contains a conversion factor to allow for the effects of household size and composition on needs in making income comparisons.
[46] Including individuals with a first or higher degree and those with a higher national certificate/diploma or teaching qualification.

reference category is individuals with qualification other than higher[47]. As stated in reviewing the theoretical models, the *a priori* expectation of education, which eventually correlates with medical knowledge, is ambiguous[48].

As with Colle and Grossman (1978), we introduce three 0-1 dummy variables for ethnic group the respondent belongs to: BLACK =1 if the individual is black, either Caribbean, African or other; INDIAN if he/she is indian, pakistani or bangladeshi and OTHER if the individual belongs to some other ethnic group. Reference category is white/european individuals. These covariates control for differences in health care utilisation between white/European and memberships of a different ethnic group that are not due to differences in the other independent variables.

According to Feldstein (1979), single persons generally use more health care. To test this proposition, I also include three dummy variables for different marital statuses: child under 16 years old (CHILD<16=1); married or living as a couple (MARRIED=1) and divorced, separated or widowed (DIVSEPWI=1). Reference category is single people. For Feldstein's claim to be data consistent, the coefficient of the last two covariates should be found significantly positive whereas children under sixteen should not behave different from single people.

Finally, following Deb and Trivedi (1997), in order to control for behavioural differences across geographical regions, country of origin is included as two 0-1 dummies for individuals coming from countries other than England (SCOT and WALES). Reference category is English people.

***Health status measures**

As a proxy for long-term status, I use a self-assessed health question which asks the individual to rate their health on average over the last twelve months relative to someone of their own age[49]. This variable is coded as excellent, good, fair, poor and very poor.

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[47] This variable summarise, amongst others, the following categories in the questionnaire: nursing qualification, GCE A levels, GCE O levels or equivalent, clerical o commercial qualifications; CSE 2-5 or Scottish Standard Grade ; recognised trade apprenticeship and any other qualifications.

[48] See Grossman (1972); Muurinen (1982) and Wagstaff (1982; 1986).

[49] It should be remarked here that it is likely the self-reported health index has a measurement error that is correlated with the number of visits, as people who have recently visited a doctor may underreport their general health. However, treating health status index as an endogenous variable is beyond the scope of this thesis thus

Following Contoyannis and Rice (2000) I created three dummy variables[50] (SAHEX, SAHGOOD and SAHPOOR) equal to one if an individual has excellent, good or fair or worse health[51]. The reference category is individuals reporting good health. Under fairly weak assumptions, Grossman (1972) and Phelps (1973) show that the quantity of medical care demanded will rise as health falls hence it is expected that the coefficient on the excellent variable will be negative and the one on the fair or worse variable positive, as the probability to visit a GP is increasing in perceived ill health.

I also use a composite measure (GHQ1) derived from the results of the reduced version of the Goldberg's General Health Questionnaire (GHQ) included in the self-completion questionnaire. This consists of twelve questions[52] concerning the general well being of the respondent. The questionnaire was originally developed to assist in the identification of respondents with non-psychotic psychiatric illness but it is often used as an indicator of subjective well-being. The respondent is asked to indicate on a four point ordinal scale (0 to 3) how they have *recently* felt with respect to the item in question. The Likert scale which we employ obtains an overall score, ranging from 0 (the least distressed) to 36 (the most distressed), which is the sum of the responses to each question, attaching values of zero to the best state and three to the worst. For the same reason as stated above, we expect the coefficient on this variable to be positive.

Further I include a third measure of subjective well-being, a measure of the self-perceived energy compared with people of the same age. This is entered as a dummy variable (ZESTLESS) and equals one if the individual finds himself less energetic than people of his same age and zero if he/she states to be more energetic or about the same.

Gender and age are included in the model, which, according to Gerdtham (1997 p.306) "… *may capture imperfect measures of morbidity for individuals of different ages or*

exogeneity will be assumed. See Windmeijer and Santos Silva (1997) for a treatment of health status as a potentially endogenous variable.

[50] Following Kenkel (1995) we initially set out by using an ordered categorical variable maintaining the initial coding and increasing in self-assessed health. Using the five initial categories, however, resulted in very poor predictions. In any case, a categorical measure is undoubtedly suboptimal. As Dasgupta (1993) notes, "A person's state of health can take a continuum of values".

[51] Recoding was performed on the same basis as in Contoyannis and Rice (2000): the categories poor and very poor contained (in total) less than 4% of the observations in our sample.

[52] The twelve individual elements of the shortened GQH are: concentration, sleep loss due to worry, perception of role, capability in decision-making, whether constantly under strain, perception of problems in overcoming difficulties, enjoyment of day-to-day activities, ability to face problems, loss of confidence, self-worth, general happiness, and whether suffering depression or unhappiness.

sex (e.g. obstetric charges"). Gender is represented by a 0-1 dummy for male, which means that females are the reference category. As it is common use, I use a cuadratic parameterisation of age on utilisation.

I also include number of children in the household by age using three dummies for age groups: 3-4 years (CHILD4); 5 to 11 years (CHILD511) and 12 to 18 years (CHLD1218). The reference category is pre-school children (up to and including two years). According to Colle and Grossman (1995), an increase in the number of children in a family lowers the quantity of care demanded[53]. They also claim visits to physicians fall with age. Therefore we expect a negative coefficient for all the three dummies.

Following Pohlmeier and Ulrich (1994), to capture the incidence of an illness in the previous year we include a dummy variable (HOSPYES) taking value one whenever an individual was hospitalised during that period.

Further, we use two dummy variables to indicate whether the individual is a current smoker or not. Reference category is non-smokers. A concern here, as remarked by Contoyannis and Jones (1999), is the long latency period involved in the consumption of tobacco and the development of respiratory and other health problems. A measure of time smoking is likely to have more explanatory power. Since smoking has been proved to seriously damage health, a positive sign is expected for the coefficient of this variable.

Our last set of covariates, following Windmeijer and Santos Silva (1997), relate to short term health. First we create two dummy variables referring to whether health limits in any way daily activities compared to most people of the same age of the respondent (LIMDAY=1 if health limits in some way daily activities[54]) or not (NOLIMDAY=1 if health does not limit daily activities at all). Following Cameron et al (1988) and Gerdtham (1997), for further account for need (=morbidity), another health status variable measuring chronic conditions of the respondent is included. Individuals were asked whether they had health problems or not at all. Respondents reporting health problems were asked a further question identifying the type of problem. I create two 0-1 dummies; the first (HLPROB) for individuals reporting health problems (any of the twelve types included in the questionnaire)

[53] We should remark that the number of children may be considered as an endogenous variable, but to treat it in such manner is beyond the scope of this thesis. Moreover, although in a somewhat different context, Tomes (1978) reports similar estimates whether the number of children is treated as exogenous or endogenous

and the other for those reporting no health problems at all (HLPRB0). Further, I also create two dummy variables for whether health limits type or amount of work (LIMWORK) or not (LIMNOT). We include LIMDAY, HLPROB and LIMWORK in the model thus we standardise the dummies on "non-chronic conditions". Obviously it is expected a positive sign for the coefficient of all these covariates since it is likely people suffering from limiting conditions visit the physician more often.

Table 2: Sample frequency distribution of the number of physician (GP) visits (number of observations= 7881)

NVISIT		Frequency	Distribution of visits (%)	Cumulated
Interval	Code			
None	1	2039	25.93	25.93
1 or 2	2	3132	39.83	65.76
3 to 5	3	1563	19.88	85.63
6 to 10	4	623	7.92	93.55
More than 10	5	507	6.45	100.00
	TOTAL	7864	100.00	
Mean		2.2913		
Variance		1.2703		
Variance/mean		0.5544		

The frequency distribution of physician visits are presented in Table 2 and the descriptive statistics for the estimation sample in Table 3. Some of the characteristics of the raw data on physician visits are as follows: 25.93% of 7864 respondents interviewed had zero visits, 39.83% had one or two visits, 19.88% between three and five visits; 7.92% six to ten and the remainder more than ten visits.

Table 3: Sample descriptive statistic

Variable	No. of observations	Mean	Std. Deviation	Minimum	Maximum
NVISIT	7864	2.2913	1.1271	1	5
SOCIO-ECONOMIC CHARACTERISTICS					
MALE	7881	0.5177	0.4997	0	1
AGE	7881	44.5752	17.9335	16	97
AGE2	7881	2308.52	1756.25	256	9409
CHILD<16	7881	0.0013	0.0356	0	1
MARRIED	7881	0.6705	0.4701	0	1

[54] Persons reporting health limits their daily activities were then shown a card with a list of physical activities (e.g. doing the housework; climbing stairs; dressing themselves…etc) to tell which of them health hinders.

Table 3 (cont.): Sample descriptive statistic

Variable	No. of observations	Mean	Std. Deviation	Minimum	Maximum
SOCIO-ECONOMIC CHARACTERISTICS					
DIVSEPWI	7881	0.1349	0.3416	0	1
HDEGREE	7881	0.0836	0.2768	0	1
NO QUAL	7881	0.4012	0.4902	0	1
JOBST1	7881	0.0902	0.2865	0	1
JOBST2	7881	0.6169	0.4862	0	1
JOBST4	7881	0.2303	0.4210	0	1
JOBFT	7881	0.1608	0.3673	0	1
SCOT	7881	0.0940	0.2919	0	1
WALES	7881	0.0485	0.2148	0	1
EHHINC	7881	16403.07	10669.29	109.0909	119060.3
BLACK	7881	0.0114	0.1063	0	1
INDIAN	7880	0.0122	0.1097	0	1
OTHRACE	7880	0.0076	0.0869	0	1
CHILD4	7881	0.1062	0.3081	0	1
CHILD511	7881	0.1622	0.3686	0	1
CHILD1218	7881	0.1630	0.3694	0	1
HEALTH STATUS MEASURES					
SAHEX	7875	0.3062	0.4609	0	1
SAHPOOR	7881	0.2304	0.4211	0	1
ZESTLESS	7831	0.1190	0.3238	0	1
LIMWORK	7875	0.1374	0.3443	0	1
HOSPYES	7879	0.0943	0.2923	0	1
SMOKES	7881	0.2924	0.4549	0	1
GHQ1	7881	10.4716	4.6218	0	36
LIMDAY	7877	0.1051	0.3067	0	1

5.- Analysis of Results

We begin with the results for the full sample. Table 4 presents the estimation results with the covariates included for number of physician visits.

Table 4: Alternative estimates for the frequency of physician visits.

Variable	(1) OLS (linear)	(2) OLS (log)	(3) Ordered probit (linear)	(4) Ordered probit (log)	(5) Ordered logit (linear)	(6) Ordered logit (log)	(7) Grouped data (linear)	(8) Grouped data (log)
Constant	2.408991	.7894975	-	-	-	-	2.768473	.7462005
	(25.505)	(8.441)					(10.536)	(3.683)
SOCIO-ECONOMIC CHARACTERISTICS								
MALE	-.294997	-.1362459	-.3514345	-.3514788	-.6070664	-.6073172	-.7039396	-.2936229
	(-12.764)	(-12.941)	(-12.882)	(-12.884)	(-12.888)	(12.893)	(-10.970)	(-12.899)
AGE	-.022004	-.0111264	-.0277927	-.0274438	-.0465427	-.0459151	-.0448337	-.0223229
	(-5.390)	(-5.971)	(-5.813)	(-5.728)	(-5.608)	(-5.519)	(-3.943)	(-5.565)
AGE2	.0002119	.0001079	.0002672	.000263	.0004511	.004436	.0004241	.0002137
	(4.835)	(5.390)	(5.221)	(5.126)	(5.057)	(4.958)	(3.469)	(4.973)
CHILD<16	-.2414606	-.0941811	-.251915	-.2502454	-.4222486	-.4195594	-.6378122	-.2259205
	(-.820)	(-.702)	(-.719)	(-.714)	(.466)	(.469)	(-.790)	(-.736)
MARRIED	.1258832	.0621452	.1578735	.1587247	.266288	.2678393	.2739488	.12951
	(3.647)	(3.952)	(3.873)	(3.893)	(3.800)	(3.822)	(2.864)	(3.789)
DIVSEPWID	.0786565	.0341654	.0915479	.0917905	.1474123	.1477465	.218071	.074191
	(1.747)	(1.665)	(1.727)	(1.731)	(1.616)	(1.619)	(1.743)	(1.669)
HDEGREE	.0050288	.0149004	.0189818	.0251591	.0372372	.0477707	-.0541693	.0133165
	(.125)	(.819)	(.398)	(.533)	(.465)	(.603)	(-.486)	(0.337)
NO QUAL	-.0168698	-.0154691	-.0272161	-.0300452	-.0645932	-.0695632	.0062062	-.0213265
	(-.647)	(-1.296))	(-.884)	(-.972)	(-1.219)	(-1.307)	(.086)	(-.823)
JOBST1	-.1589645	-.0694631	-.1875999	-.1835442	-.3316965	-.3243998	-.3847035	-.1553739
	(-2.807)	(-2.692)	(-2.793)	(-2.732)	(-2.872)	(-2.808)	(-2.450)	(-2.758)
JOBST2	-.1050839	-.0394692	-.1113106	-.1069847	-.1955941	-.1877663	-.290698	-.0955409
	(-2.259)	(-1.840)	(-2.030)	(-1.927)	(-2.070)	(-1.963)	(-2.249)	(-2.052)
JOBST4	-.0147308	-.0115089	-.0214595	-.0209056	-.0670182	-.065671	-.0031915	-.0151281
	(-.253)	(-.434)	(-.314)	(-.306)	(-0.567)	(-.554)	(-.020)	(-.264)
JBFT	.0030085	.009333	.0188896	.0172591	.0191166	.0162477	-.0560744	.0095667
	(.095)	(.650)	(.511)	(.467)	(.303)	(.258)	(-.642)	(.309)
SCOT	.0997868	.0331693	.1049127	.1041046	.1826927	.181405	.3284532	.0940952
	(2.753)	(2.008)	(2.462)	(2.442)	(2.478)	(2.460)	(3.259)	(2.634)
WALES	.0189805	-.0031213	.0083177	.0068871	.0098488	.0071473	.1281261	.0120938
	(.389)	(-.140)	(.144)	(.119)	(.099)	(0.072)	(.944)	(.250)
EHHINC	7.73e-07	.0028246	1.00e-06	.0027519	1.73e-06	0.00413	-7.17e-07	.0016757
	(.675)	(.302)	(.741)	(.114)	(.748)	(.100)	(.226)	(-.083)
BLACK	-.0210316	-.0011038	.0163982	.0150591	.0370969	.03406	.1243126	.0207472
	(.210)	(-.024)	(.139)	(.127)	(.180)	(.165)	(.446)	(.209)
INDIAN	-.0174131	-.0002287	-.0000168	-.0018759	.0243296	.21147	-.0975584	-.0035162
	(-.181)	(-0.005)	(0.000)	(-0.017)	(.128)	(.111)	(–.367)	(-0.037)
OTHER	-.0494931	.0328647	.070117	.0690117	.1272379	.1251947	.0276267	.0456688
	(.411)	(.599)	(.496)	(.488)	(.524)	(.516)	(.083)	(.386)

Table 4 (cont.): Alternative estimates for the frequency of physician visits.

Variable	(1) OLS (linear)	(2) OLS (log)	(3) Ordered probit (linear)	(4) Ordered probit (log)	(5) Ordered logit (linear)	(6) Ordered logit (log)	(7) Grouped data (linear)	(8) Grouped data (log)
CHILD4	.1744852 (4.586)	.063195 (3.640)	.186884 (4.17)	.1832097 (4.082)	.3230775 (4.187)	.316278 (4.097)	.5367724 (5.087)	.1597675 (.000)
CHILD511	-.0635489 (-2.042)	-.0275552 (-1.940)	-.0712614 (-1.936)	-.0748878 (-2.031)	-.1297881 (-2.063)	-.1361288 (-2.161)	-.1743645 (-2.025)	-.0631592 (-2.044)
CHLD1218	-.0531996 (-1.743)	.-.0218384 (-1.569)	-.0614261 (-1.698)	-.0637491 (-1.761)	-.0986832 (-1.604)	-1.027372 (-1.668)	-.1473185 (-1.746)	-.0561182 (-1.851)
HEALTH STATUS MEASURES								
SAHEX	-.2649206 (-10.566)	-.1391688 (-12.189)	-.3565324 (-11.849)	-.3556328 (-11.824)	-.6090675 (-11.862)	-.607421 (-11.835)	-.4818523 (-6.976)	-.2884545 (-11.493)
SAHPOOR	.5712384 (18.884)	.2213925 (16.032)	.5803748 (16.479)	.5799447 (16.466)	1.022601 (16.527)	1.021854 (16.513)	1.679858 (19.821)	.5077197 (17.376)
ZESTLESS	.1690748 (4.618)	.0565195 (3.389)	.1671732 (3.930)	.1674344 (3.936)	.2939771 (3.979)	.2944324 (3.985)	.599409 (5.837)	.1504905 (4.222)
LIMWORK	.2852889 (6.955)	.0985402 (5.273)	.280047 (5.929)	.2791225 (5.909)	.5247351 (6.318)	.5229375 (6.296)	.947644 (8.217)	.2493456 (6.302)
HOSPYES	.6681339 (18.107)	.2565399 (15.264)	.6999815 (16.236)	.701206 (16.266)	1.194027 (15.735)	1.195652 (15.756)	2.052297 (19.647)	.6086637 (16.975)
SMOKES	-.085815 (-3.581)	-.0433006 (-3.963)	-.1085445 (-3.834)	-.1095103 (-3.865)	-.197121 (-4.051)	-.1988928 (-4.084)	-.1825549 (-2.746)	-.0904452 (-3.809)
GHQ1	.0133577 (5.464)	.0054029 (4.852)	.0150085 (5.232)	.014986 (5.224)	. 0259994 (5.240)	.0259632 (5.233)	.0390564 (5.720)	.129123 (5.372)
LIMDAY	.1227005 (2.632)	.0302566 (.154)	.0991948 (1.848)	.0999613 (1.863)	.1775984 (1.887)	.1787774 (1.899)	-.5437793 (0.000)	.099006 (2.199)
HLPROB	.3603756 (15.082)	-.1788895 (16.434)	.4516759 (15.920)	.4517189 (15.921)	.7691919 (15.751)	.7695113 (15.755)	.7468865 (11.314)	.3696505 (15.675)
Sigma. 95% Conf. Interval	-	-	-	-	-	-	2.4714 2.5582	.8352 .8709
No. observat.	7777	7777	7777	7777	7777	7777	7777	7777
No. iterations	-	-	4	4	5	5	4	5
-Log- L	-	-	9591.2585	9591.5268	9605.6153	9605.8898	15978.074	11437.046
R-squared	(adj) 0.3265	(adj) 0.42108	(pseudo) 0.1284	(pseudo) 0.1284	(pseudo) 0.1271	(pseudo) 0.1271	N/A	N/A
Overall sig. Prob > χ^2	F(30,7746 126.67 = . 0000	F(30,7746 105.89 = . 0000	$\chi^2(30)$ = 2827.05 = .0000	$\chi^2(30)$ = 2826.51 = .0000	$\chi^2(30)$ = 2798.34 = .0000	$\chi^2(30)$ = 2797.79 = .0000	$\chi^2(30)$ = 3083.11 = .0000	$\chi^2(30)$ = 2949.25 = .0000
RESET2 Prob > $\chi^2(1)$	t (7745) = 1.364 = .173	t (7745)= -2.023 = .043	$\chi^2(1)$ = 1.49573 = 0. 221	$\chi^2(1)$ = 1.42086 = 0.233	$\chi^2(1)$ = .58217 = 0. 446	$\chi^2(1)$ = .53436 = 0.465	$\chi^2(1)$ = 48.678 = 0. 0000	$\chi^2(1)$ = 0.0471 =.829
Hetero Prob > $\chi^2(1)$	-	$\chi^2(1)$ = 0.12 = 0.7269	-	-	-	-	$\chi^2(1)$= 5.01 = 0. 0252	-

Notes:
1. The baseline individual in all models is male; single; has qualification but not higher degree; with children under 2 years old, is unemployed, belongs to white/European ethnic group; lives in England, reports good health, feels about the same or more energetic that people of him same age, is non-smoker, declares to have no health problems and health does limit either daily activities or type/amount of work. Also he was not hospital inpatient during the year before the interview.
2. Coefficients reported for all models are the coefficients on x in the index function xβ. t- ratios are in parentheses. Critical values for t-student distribution are 1.65; 1.96 and 2.576 at the significance levels 10%, 5% and 1% respectively.
3. For the ordered probit and logit models, the cut-off points are estimated as

	Ord. Probit (lin)	Ord. Probit(log)	Ord. Logit (lin)	Ord. Logit (log)
μ_1 =	-1.0376	-1.0201	-1.7695	-1.7454
μ_2 =	.2408	0.2576	0.3854	0.4093
μ_3 =	1.0956	1.1123	1.8735	1.8973
μ_4 =	1.6994	1.7162	2.9806	3.0044

Interestingly we find that most of the specifications cannot be rejected as appropriate models of the determinants of health care utilisation according to the RESET test at the 1% level. Only for the grouped data regression in the linear form is the RESET statistic significant. However, there is no evidence of heteroskedasticity in the errors, based on the test used.

In general the estimated coefficients do exhibit the expected signs except for those corresponding to the covariates on education. However these effects appear not to be significant.

Since the grouped data regression approach is theoretically more appealing and the estimated effects quite similar[55], the following discussion concentrates on the results of the estimated coefficients for this model in the logarithmic form. Moreover, even though ordered probit and ordered logit models passed the RESET test, we get a negative estimate for the first of the ancillary parameters (μ_1 in Table 4). Therefore, following Maddala (1983), we can assume there is some specification error in these models, which is not picked up by the general check used.

[55] We should bear in mind that the estimates of the parameters are not directly comparable. Since the logistic distribution has a variance $\pi^2/3$, the estimated coefficients obtained from the logit model have to be multiplied by $\sqrt{3}/\pi$ to be comparable to the estimates obtained from the probit model. Amemiya (1981) suggests that the logit estimates be multiplied by 1/1.6 = 0.625 produces a closer approximation between the logistic and the distribution function of the standard normal.

As stated in section 3, the estimated coefficients for the ordered response models do not give the estimated marginal impacts of changes in the independent variables on the predicted value of the dependent variable. Manipulation of the coefficients at a certain value of the mean function is required to estimate the marginal impact of each variable on the probabilities of each group[56]. The only prediction which can be made from the reported coefficients is that is the coefficient is positive, the probability of the highest group will increase and the probability of the lowest will decrease (the opposite being true if the coefficient is negative). The impact on the other groups cannot be predicted from the reported coefficients.

As stated above, most of the estimated coefficients have the expected sign. The influences of personal characteristics are found to be significantly different from zero. We find familiar results: men are less likely to use medical care than women and there is a strong convex relationship between the number of consultations and age[57].

We do find enough evidence favouring Feldstein’s proposition (1979). The effect of not being single is estimated positive and it is clearly significant. Thus single people appear to visit the GP less often than married or divorced/widowed whereas there are not significant behavioural differences between the former and children under 16 years old (supposedly never married as well)

The estimated relationship between age of children in the household and number of GP visits is not monotonic. With respect to the reference category (children under two years), probability of visiting a physician is first increasing for children up to four years old; then it decreases for dependent children between five and eleven years. For children over twelve years old we also find an increased probability to visit compared with children less than two years but the effect is only significant at the 10% significance level.

Membership of other than white/european ethnic group appears not to affect number of GP consultations. For all of the three dummies included the coefficients are not significant at any traditional significance level. Thus, there is enough evidence against a

[56] A nice exercise to analyse marginal effects could be to graphically represent how the probability distribution changes as, ceteris paribus, each covariate do so.
[57] Cameron et al. (1988) also find an inverted bell shaped age pattern for doctor consultations using an instrumental variable estimator.

potential selectivity process with non-white people more likely to visit "public care" sites (hospital, emergency rooms, hospital outpatient departments and public clinics not connected with hospitals) or, alternatively, against a lower latent health status for races other than white.

Wagstaff's (1986, p.216) argument that people with a higher education can improve their health more efficiently and therefore would contact a GP less often cannot be ruled out in these data. Although individuals having a higher qualification, mainly a first or a higher degree, are estimated to be significantly more likely to talk or visit the GP than those with other type of qualification, this effect is clearly not significant. Moreover, despite non-qualified people appearing to be less likely to visit the GP, the effect is clearly not significant.

Health care utilisation appears quite unresponsive to changes in the level of income. A small positive and not significant coefficient is found for this covariate, thus, conditional on the other variables in the model, the hypothesised negative effect of income (meaning greater opportunity costs the higher the level of income) are not borne out in these data.

The dummies for self-employment status (JOBST1) and in-paid employed (JOBST2) have a negative significant effect, which is consistent with *a priori* expectations. Self-employed as well as in-paid employed people are estimated to be less likely to visit a doctor than the unemployed, with the effect being greater for those in self-employment. However we do not find significant differences between the unemployed and people on maternal leave, retired or other job situations. Interestingly we find a positive but not significant effect of full-time employment compared to part-time. Therefore plausible greater stress related illnesses for individuals in full-time employment leading to higher frequency of GP visits is ruled out in our sample.

The estimated effect of the dummies for non-English people is positive and significant for Scottish people and negative but not significant for Welsh. The different behaviour for Scottish people, estimated to be more likely to visit a GP than English, may be explained by looking at Public Heath statistics[58]. Scotland shows higher than the average mortality rates from many diseases such as lung cancer or coronary heart disease hence there are good reasons to support this finding here. Although the determinants of these regional

[58] See, e.g. Public Health Common Data Set.

differences in health behaviour are beyond the scope of this thesis, it appears to be an interesting subject to explore in future research.

Not surprisingly, the frequency of physician visits is clearly responsive to need, proxied by morbidity. The estimated effects pertaining to the dummies for self-assessed health (SAHEX=1 and SAHPOOR=1) are significant at the 1% level. The effects of excellent health is estimated to be much smaller than for fair or worse health and in the opposite directions. Individuals reporting excellent health are less likely to visit the doctor than those claiming that their health is good whereas reporting own health is just fair or worse has a positive effect in the probability of visiting a GP. We also find a significant positive effect for those individuals reporting their energy is less than people of their own age. Also, as expected, the higher the score in the General Health Questionnaire the higher the probability of a GP visit, although the effect shown is not very large.

It is not surprising either that people who were seriously ill in the previous year, thus hospitalised, require more treatment from general practitioner. This may be indicative of low latent, unobserved health or, alternatively, may be due to post-hospitalization on-going care provided through their general practitioner (such as follow-up for prescriptions, monitoring of health status, … etc).

Unexpectedly we find a significant negative effect of being a smoker on the number of GP consultations. A plausible explanation of this finding is that smokers know that this habit seriously damage their health and that they will be told to stop by physician. Thus they tend to avoid visiting the doctor for minor illness spells.

Consistent with previous studies individuals whose health limits type or amount of work are found more likely to visit the doctor than those without work limiting conditions. Also the probability of a GP visit by people reporting chronic diseases is estimated to be significantly higher than the probability of doing so by people declaring to have no health problems at all. Moreover, as expected, the effect of limitations in daily activities due to health is found to be significant and positive.

Although using a different modelling approach, in general, our results for the full sample are in line with those found for the UK by Windmeijer and Santos Silva (1997), for Australia by Cameron et al. (1988) and for Germany by Pohlmeier and Ulrich (1995).

For the model of choice, next we further split the sample by gender. Accordingly, Table 5 presents the estimation results for males and females separately.

In general, the results by gender are very similar to those using the full sample, with some noteworthy exceptions for the covariates related to socio-economic characteristics. We find that smoking appears not to affect number of GP consultations for females. One explanation of this result could be that this is quite a new habit for women, and given the long latency period involved in the consumption of tobacco and the development of respiratory and other health problems, the effect on females' frequency of GP visit is insignificant.

Another remarkable difference relates to job status. As expected, the dummy for other job status, including maternal leave (JBST4), turns out to be significant for females. The negativity of the effect can be easily understood bearing in mind that these women tend to favour specialists over general practitioners.

Finally, male Scottish people cannot be said to behave differently than their English counterparts. Therefore the higher probability of visit to the doctor for Scottish people found for the full sample may be attributed just to women. A reasonable explanation for this result seems to be that the morbidity measures do not fully reflect health status, which is likely to be lower for Scottish people.

Table 5: Logged grouped data regression estimates for the frequency of physician visits by gender

Variable	MALES	FEMALES
Constant	.341097 (2.713)	.9891496 (7.237)
SOCIO-ECONOMIC CHARACTERISTICS		
AGE	-.0203548 (-3.541)	-.0226676 (-4.058)
AGE2	.0002394 (3.853)	.00001676 (2.837)
CHILD<16	.1732849 (.395)	-.515685 (-1.314)
MARRIED	.1172094 (2.477)	.1067435 (2.160)

Table 5(cont.): Logged grouped data regression estimates for the frequency of physician visits by gender

SOCIO-ECONOMIC CHARACTERISTICS		
DIVSEPWID	.0600997 (.885)	.1235611 (2.077)
HDEGREE	-.0357562 (-.694)	.0499175 (.809)
NO QUAL	-.0438303 (-1.263)	.0301179 (-.793)
JOBST1	-.1016971 (-1.545)	-.3155215 (-3.002)
JOBST2	-.0317112 (-.579)	-.2785195 (-3.332)
JOBST4	.0465925 (0.628)	-.1748782 (-1.828)
JBFT	-.0066856 (.103)	-.0017624 (-.046)
SCOT	.12499 (.243)	.1515139 (3.083)
WALES	.0270687 (.407)	-.0075048 (-.108)
EHHINC	5.5657e-04 (.143)	4.0425e-04 (1.065)
BLACK	.0605584 (.444)	.010043 (.070)
INDIAN	-.0207061 (.181)	-.0064523 (.039)
OTHER	.2035128 (1.325)	-.140156 (-.779)
CHILD4	.0645963 (1.331)	.3341442 (5.606)
CHILD511	-.0051237 (-.123)	-.1190271 (-2.619)
CHLD1218	-.0305043 (-.741)	-.0759252 (-1.728)
HEALTH STATUS MEASURES		
SAHEX	-.2629872 (-7.783)	-.3183492 (-8.646)
SAHPOOR	.4941399 (12.342)	.5226777 (12.421)
ZESTLESS	.1311994 (2.641)	.1659389 (3.285)
LIMWORK	.3038804 (5.551)	.1983366 (3.524)
HOSPYES	.5467206 (10.029)	.5934163 (12.367)
SMOKES	-.1276851 (-3.961)	-.0511236 (-1.482)
GHQ1	.0107417 (3.220)	.0141733 (4.149)

Table 5(cont.): Logged grouped data regression estimates for the frequency of physician visits by gender

HEALTH STATUS MEASURES		
LIMDAY	.0845675 (1.335)	.1190271 (1.885)
HLPROB	.3513169 (10.887)	.3676692 (10.784)
Sigma. 95% Conf. Interval	.8024397 .8523017	.8375869 .8876305
No. observat.	4024	3753
No. iterations	5	5
-Log- L	5563.4294	5817.3595
Overall sig. Prob > χ^2	$\chi^2(29) =$ 1380.46 = 0.0000	$\chi^2(29) =$ 1405.34 = 0.0000
RESET2 Prob > $\chi^2(1)$	$\chi^2(1) = 0.50$ = 0.4800	$\chi^2(1) = .23$ = 0.6298
See notes on Table 4.		

6.- Conclusions

Recognising that what the consumer demands is health and not health care, and thus, that the demand for health care is a derived demand constituted a fundamental attainment. However, in an era in which the share of the public budget taken by health care rises, it becomes increasingly important to determine those factors influencing the demand for medical services and the decision process underlying it. The basic question we have tried to solve in this paper is: **What basic forces influence the utilisation of health care services?** Finding the answer may be crucial to improve the health system in general and particularly for resource allocation, to make it more equitable and adjusted to need. Moreover, answer can help to understand causes underlying the spectacular increase of health care public expenditure over the last thirty years.

It is commonly accepted that directly applying the conventional theory of demand to health and health care leads to wrong conclusions. Hence, the usual microeconomic approach needs to be altered due to the peculiarities of the sector.

Therefore, in this thesis, as with other empirical studies, we redefine health care consumption in terms of **utilisation**, allowing proper acknowledgement of the influence of the supplier as well as of the role of health insurance. We make use of General Practitioner services dependable on socio-economic factors, such as age, income and education, along with proxied health status measures

Using a cross section of data from the British Household Panel Survey, we explored how alternatives estimation models perform. Grouped data regression is shown to be the most appropriate modelling approach due to the limited nature of the dependent variable. An alternative ordered probit turns out to be less efficient since it normalises the variance to one rather than producing an estimate for it from the information on the scale of the latent variable generating the observations on the dependent variable.

For the grouped data regression approach, the RESET statistic was significant in the linear form but not in the logarithmic model. The estimated regression coefficients using the latter functional form are compatible with previous studies in health care utilisation[59]. We find familiar results. Personal characteristics, such as gender, age or region of origin, significantly influence the use of medical care and, not surprisingly, the frequency of physician visit is clearly responsive to need, proxied by morbidity. Individuals that report fair or worse health and /or health problems and limitations in some way due to health are estimated to be more likely to use medical care than those self-assessing their health is good.

We also find some remarkable behavioural differences when splitting the sample by gender, as expected from the different profile of physician visits found for males and females.

However, some difficulties of interpretation remain. We have not controlled for the potential endogeneity of included explanatory variables, for example, variables measuring morbidity. Hence, our estimates may be contaminated by biases as found in previous cross-sectional analyses.

Further, the nature of the available data has dictated the modelling approach used. Possible future research might employ panel data instead of a cross-section. Panel data have many advantages: they allow an analysis of how individuals and household experience change in their socio-economic environment and how they respond to such changes; an

[59] See, e.g**.,**Windmeijer and Santos Silva (1997), for Australia by Cameron et al. (1988) and for Germany by Pohlmeier and Ulrich (1995).

analysis of how conditions, life events, behaviour and values are linked with each other dynamically over time. They also allow the analyst to control for unobserved heterogeneity and the potential for endogenity.

Moreover, more sophisticated econometric models[60] could be used such as hurdle or finite mixture models although this requires count data, i.e. data on number for consultations, instead of intervals for the dependent variable.

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[60] See 2.2. Empirical models for some examples.

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