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An Econometric Estimation of the Demand for Private Health Insurance in the UK

by

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DISCUSSION PAPER 24

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The Author

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ABSTRACT

The demand for private health insurance in the UK has risen rapidly in the last decade. The paper discusses the nature of the demand for private health insurance in a health care market dominated by a public supplier, in which the consumer may neither opt out of his contribution to the National Health Service nor lose his entitlement to free-at-point-of-delivery publically provided medical care. The demand for private health cover is estimated using data from the 1982 General Household Survey. The results indicate that income, the health and the medical services utilisation of adult members of households are significant determinants of the probability of purchase of health insurance cover. The results also suggest that we lack information on the nature of decision to take out and give up health insurance cover. The paper outlines research currently underway to collect and analyse data about health insurance purchase from a national representative sample of households.

1. INTRODUCTION

The private health sector in the UK has grown considerably since the late 1970s. Although dwarfed in terms of absolute size in comparison with the National Health Service (NHS), this comparison masks the relative contribution of the private sector to the provision of facilities for acute care in general and elective surgery in particular. Williams et al (1985) estimated that approximately 13 per cent of all domestic inpatient elective surgery in England and Wales in 1981 was carried out in the private sector. Imbalances in the distribution of private activity between specialities and geographical regions meant that this proportion rose to 26 per cent for certain operations and to 20 per cent of the total inpatient caseload in certain regions. Although some acute private health care is paid for at the point of demand, over 70 per cent of acute private care is financed by private health insurance. Private health insurance therefore plays a considerable role in determining access to private health care and so also to rapid access to treatment for acute medical care.

Although analysis of the demand for and impact of health insurance has been an important component of the examination of the economics of the health care market in health care systems in which price is the primary allocation mechanism (Phelps (1976), Keeler (1977)), and in the more 'mixed' public/private European systems (Zweifel, 1982; van de Ven and van Praag, 1981a), surprisingly little research has been undertaken in Britain into the effects of private health purchase. In this paper we analyse the demand for non-corporate private health insurance cover. The research presented here forms part of a larger study which seeks to analyse the response of consumers to the availability of private health insurance in a health care market dominated by a free-at-point-of-demand public supplier. The overall research programme will examine not only the non-corporate demand for private health insurance cover but also the response of the consumer to this cover through analysis of the demand for public and private health care of the privately insured.

Health insurance contracts in the UK may be purchased either by individuals to cover themselves and their immediate family (non corporate demand) or by companies to cover their employees and sometimes also their employees' families (corporate demand). As our study focuses upon the response of the consumer to the availability of private health insurance and as the motivation for corporate purchase may be different to the motivation for non-corporate demand, we concentrate only on non-corporate demand. The current paper presents and discusses a single equation econometric model of the non-corporate demand for private health insurance in the UK. The specification of the econometric model and choice of estimator is based on a theoretical model of demand which takes into account the limited nature of both the private health care and the private health insurance markets. The data set used for estimation is cross-sectional; the source is the 1982 General Household Survey (GHS).

The organisation of this paper is as follows. In the first section we discuss briefly the nature of the private health insurance market in the UK and the nature of demand for private health insurance. We argue that the demand for private health insurance is essentially the choice between some versus no insurance cover and the decision to purchase is derived from a comparison of the expected utility under insurance with the expected utility of no (private) health insurance. In the second section we discuss the data requirements for econometric estimation of such a model, the choice of appropriate estimator given the discrete nature of demand, and the interpretation of the estimated set of coefficients in an econometric model of choice between two uncertain prospects. In section 3, we discuss the econometric estimation, the model selection process and present some of the results. The final section outlines possible extensions to the model and implications for further research.

1. THE DEMAND FOR PRIVATE HEALTH INSURANCE

1.1 The Nature of Private Health Insurance

The growth in the private sector has been paralleled by a growth in the number of persons covered by private health insurance. Industry sources estimated that 2.2 million persons were covered in 1977, 4.2 million in 1984.

The General Household Survey estimated that approximately 7% of the population in 1982 was covered by private health insurance. Approximately half the subscriptions were non-corporate purchase (including those subscriptions purchased through a group organised but not funded by an employer) and the other half were either wholly or partly paid for by employers.

Private health insurance contracts may cover one or more members of a family, defined by the suppliers of insurance contracts as an adult plus his/her spouse and their children under the ages of 18 or 21. Although there are a number of health insurance suppliers in the market, the contracts offered are broadly similar (each company offers two or at most three policies). The benefits of all policies are reimbursement for the medical costs for certain types of treatment in the private sector; policies do not cover for the non-medical costs of illness, such as loss of pay due to time off work. The higher the premium, the higher the quality of hospital which is covered by the level of reimbursement provided by the insurance, where quality relates mainly to the non-medical attributes of treatment (eg. the hotel facilities provided by a hospital).

The policies are designed to provide full or near full reimbursement for treatment covered by the policy. Cost-sharing devices (eg. deductibles, coinsurance) are not used; instead the set of treatments covered by policies is limited. Basically cover is provided for short term inpatient care, specialist consultations and diagnostic tests. Treatments which are complements to this type of care are excluded from cover (eg. primary care, long term (over 6 months) nursing and psychiatric care and geriatric care). Further, if a purchaser has a history of a medical condition the contract he is offered may exclude cover for treatments arising from this condition.

In this market the choice of insurance is essentially a discrete choice between some and no insurance rather than the (continuous) choice of an interior optimal level of cover. If insurance is purchased, and should the individuals covered by the policy require the type of medical care that is covered by the policy, private sector care may be taken at zero or near zero cost. Purchase of insurance does not prevent (as in some other European health care systems) utilisation of the public health care system, nor does it permit individuals to 'opt out' of their contributions to public sector provision. The alternative to insurance purchase is either public sector care at zero money cost or private sector care at a positive price.

1.2 A Model of Demand

Elsewhere (Propper, 1986) we have developed a formal model of the process of choice; here we outline the process less formally. We assume the consumer chooses between the two prospects - insurance and no insurance - on the basis of expected utility of the two choices. As the health of one family member may affect the utility of other family members and as one policy may cover more than one member of the family (as defined by the insurance contract), we assume the choice making unit to be the family rather than an individual.

The expected utility of the two prospects depends on the costs and benefits of treatment in the two sectors for each state of ill health and on the expected distribution of states of ill health. Any factor which increases the costs or decreases the benefits of public relative to private care or which increases the utility of insured relative to uninsured care is likely to increase the probability of purchase.

The relative costs of care in the private and public sectors are a function of the allocation mechanisms of the two sectors. In the private sector care is allocated by money price; in the public sector care is allocated by need, and excess demand rationed by queue, either in the form of queueing in person or in the form of waiting lists. The costs of private sector care are therefore direct financial costs and the costs of NHS care are the costs of waiting. The costs of waiting are likely to be a function of the value of time of the family unit, and as waiting lists vary regionally we would also expect the costs of NHS care to depend on the decision maker's location.

The main difference in the benefits of treatment in the two sectors is derived from the greater provision in the private sector of 'consumer orientated' attributes of the medical care package, such as better hotel facilities, choice of specialist, greater information about the medical condition and its treatment. The differences in the quality of medical intervention per se is likely to be fairly small, as consultants are generally employed concurrently in both sectors and nursing staff in both sectors are drawn from the same pool of labour. The utility put on these 'consumer associated' attributes of care, and so the difference in expected utility of private and public care, is probably a function of the decision maker's knowledge of either or both health care systems and perhaps also of the political attitudes of the decision maker towards the private health care sector.

As health insurance can only be used in certain states of (ill)health, but the premium is paid before the state of health is known, the expected utility of insurance compared to the expected utility of no insurance is a function of the expected distribution of states of health. A priori, those who expect to need acute care are more likely to purchase insurance than those who do not. For any given distribution of health states the expected utility of insured relative to uninsured care will depend upon the relative net benefits of private and public care and the attitude of the decision maker to risk. For any given difference in the expected utility of care in the two sectors, the more risk averse the decision maker the more likely he is to prefer insured to uninsured private care.

On the basis of this informal discussion we expect purchase of insurance to be positively related to factors which (i) increase the relative costs of NHS care, (ii) increase the relative benefits from private sector care and (iii) increase the utility from insurance relative to no insurance. We expect NHS costs to be a positive function of value of time, and so of income, and a positive function of the length of waiting lists (and so of region). We expect the relative benefits of private care to depend firstly upon knowledge of and attitudes to care in the two sectors and secondly upon the expected distribution of health states. Finally, we expect the utility of insurance relative to no insurance to be a negative function of the cost of insurance (the premium), a negative function of the number of exclusions, a positive function of risk aversion and a positive function of the extent to which the mass of the distribution of health states is concentrated in the set of states for which insured care is available.

2. THE DATA SET AND CHOICE OF ESTIMATOR

2.1 The Data Set

In the model we have proposed the choice of health insurance is discrete. Purchase is the outcome of comparison of the expected utility of insurance in the next period with the expected utility of non-purchase in the next period. Insurance, if purchased, may cover one or more family members defined for the purposes of the contract as one or two (married) adults and their dependent children under 18 or 21 (ie. a similar definition to tax units). Given this model, an appropriate data set would include information on the income, health, employment status and insurance cover of all individuals within the decision making unit. The most appropriate data set available was the General Household Survey (GHS). The GHS is an annual cross-sectional survey of approximately 12,000 households in England and Wales. It includes information on the age, sex, education, employment, income, medical care and health insurance cover of all household members (GHS, 1982). While a household survey, family units can be identified. The health insurance variable is qualitative but since the source of expenditure is recorded, families covered by corporate policies can be distinguished from those with non corporate purchase.

For our purposes the data provided in the GHS has a number of short-comings. It contains no information on political attitudes, on attitudes towards risk and on beliefs about the benefits of the private medical sector relative to the NHS, all of which have been argued to be factors in the decision to purchase insurance. Several other variables central to the theoretical model can only be measured by proxies; the value of time (one of the key determinants of the costs of NHS care) has not been measured directly, but can only be proxied by income and measures representing the constraints on allocation of non-working time, expected health status is only partly measured by current (respondent assessed) ratings of health and measures of recent medical services utilisation. In addition, the GHS contains no data on past purchase of health insurance.

These shortcomings are to be expected when the available data are secondary surveys, designed for purposes other than that required by the analyst. However, the low incidence of health insurance purchase in the population means that collection of a large scale data set specifically designed for the analysis of health insurance is prohibitively expensive and the GHS, despite its shortcomings, is a more suitable data set than say the Family Expenditure Survey (FES), as the latter survey contains no information on medical care and measures of current health status and does not allow the distinction of individuals/families with corporate insurance cover from those with individually purchased policies.

2.2 Choice of Estimator

The observed dependent variable (whether or not a family unit has purchased health insurance cover) is binary. For statistical reasons an estimator appropriate to a qualitative response model should be used. Probit and logit models are frequently used to estimate models in which the observed dependent variable is discrete although the underlying theoretical dependent variable may be continuous. However, in the model of choice of health insurance, the underlying theoretical choice is discrete, as family units either purchase or do not purchase health insurance cover. Under certain specifications of the functional form of the utility function, the choice of logit or probit estimator for the econometric analysis of the demand for health insurance can be derived from a theory of utility maximisation.

In an extensive discussion of choice between known outcomes McFadden (1974, 1975, 1981) has shown that if utility is specified as a random variable which is additively separable into a deterministic and a random component, the choice of econometric estimator depends on the analyst's a priori assumptions about the probability distribution of the random component. Further, if the deterministic component can be specified as a linear function of (known) functions of the choice attributes and socio-economic characteristics of the choice maker, the estimated coefficients of the econometric model can be interpreted as the weights given to each (function) of these attributes and socio-economic characteristics in the probability of choice of option.

The McFadden model discusses choice between certain alternatives; the choice between insurance and no insurance is a choice between two uncertain prospects. To provide a link between the statistical model of insurance purchase with utility maximisation, the McFadden discussion of random utility has to be extended to choice under uncertainty. We outline the McFadden model and discuss possible extensions in Appendix 1; here we present only a summary.

While there is considerable evidence that individuals choosing between uncertain prospects make errors of judgement in the choice process, there is currently less agreement as to how this is best modelled in an economic framework (see, for example, the review by Machina, 1983). If a random utility approach is adopted, there are several ways this approach can be applied to choice under uncertainty, but it is not clear which application is most plausible.

Under two very simple extensions of random utility to choice under uncertainty which (i) allow separation of expected utility into a deterministic and a stochastic component, and (ii) the specification of the deterministic component of the utility function as a linear combination of attributes of the choice and of the decision maker, the estimation of a probit or logit model of choice between two uncertain prospects can be linked to utility maximisation if it is assumed that the deterministic component of utility depends on the state only through the attributes of choice and decision maker in each state. This in turn implys state independent utility functions.

In such a specification the random component of expected utility can be interpreted as a weighted distribution of differences in the errors associated with each of the two choices, where the weights are the fixed probabilities given to the occurence of each state.

2.3 Choice of Probability Distribution

We have assumed that choice of health insurance is the outcome of utility maximisation with random error. As a result of errors in optimisation, the decision maker calculates the expected utility of each of the two prospects with some error. This error is assumed uncorrelated with the expected utility of each prospect. A difference in these two errors can be calculated, and this difference in errors will have a certain distribution. The choice of econometric estimator implies certain assumptions about the nature of this distribution. If this difference is assumed normally distributed a probit model should be estimated; if assumed logistically distributed, a logit model is appropriate. The probit and logit models are virtually indistinguishable except at the tails of the two distributions, where the probit model approaches the extreme values more rapidly. Since the decision to purchase health insurance is made only once a year, we assumed the error associated with the calculation of the expected utility of each of the two prospects could be large and so a distribution of differences in errors with greater weight in the tails was preferred to one with less. Accordingly, we choose to use a logit estimator.

2.4 Choice Based Sampling

Estimation was carried out using a sample of observations from the 1982 GHS. The unit of analysis was the family, as defined in health insurance contracts; the dependent variable was binary, equal to one if the family had individually purchased cover for one or more family members and zero otherwise. As the proportion of families in the 1982 GHS with positive individually purchased cover is under 5%, a random sample (say 10%) of the GHS would give insufficient information on observations with a dependent variable with a value of one. We therefore selected a sample by first stratifying observations (family units) into two groups on the basis of the dependent variable and then selecting different sized random samples from each group of family units.

This procedure is referred to in the econometric literature as choice based or endogenous sampling (Manski and McFadden, 1981b). While the aim of exogenous or endogenous sampling is the same - to attain more information on the decision to undertake an action, the likelihood functions in the two schemes, and so the appropriate MLE estimators, differ. The likelihood function for exogenous sampling is given by:

$$L_e = \pi p(j_i | x_i, \beta) g(x_i) \qquad (1)$$

and the likelihood function for choice based sampling by:

$$L_c = \pi p(j_i | x_i, \beta) f(x_i) H(j_i) Q^{-1}(j_i | \beta) \qquad (2)$$

where

$P(j_i|x_i)$ = conditional probability the jth alternative is chosen, give the exogenous variables x_i

$f(x_i)$ = true density of x_i

$g(x_i)$ = density according to which researcher draws x_i (known)

$Q(j)$ = distribution of j dependent on β

$H(j)$ = probability according to which the researcher draws j

j indexes the choices, i the individual.

The choice of estimator for endogenous sampling depends whether f(x), the marginal distribution of exogenous variables and Q(j), the marginal distribution of choices in the population is known or unknown (Manski and McFadden, 1981a). If it can be assumed that Q(j) is known, the task of estimation is simplified considerably. In the present case, it was assumed that Q(j) was known, that the GHS is a sufficiently large sample of the population that the true distribution of health insurance purchase in the population is the same as the distribution in the GHS. It was assumed that the true distribution of f(x) was unknown; as x includes several variables which are multi-dimensional transformations of the raw population variables it is unlikely f(x) is known. (For example, an important determinant of the expected utility of health insurance is the value of time. Although a function of income, the distribution of which may be known, the distribution of value of time in the population is not known).

If Q(j) is assumed known and f(x) assumed unknown, the likelihood of drawing an individual who has made choice j, conditional on exogenous variables x, is

$$P(j|x,\beta)f(x)Q^{-1}(j|\beta_o)\ H(j) \tag{3}$$

where $Q(j|\beta_o)$ denotes the true (and known) distribution of j, (other symbols as above). The likelihood function for choice based sampling becomes

$$L_c = \pi\, p(j_i|x_i, \beta)f(x_i)H(j_i)Q^{-1}(j_i|\beta_o) \tag{4}$$

To estimate the parameters of this likelihood, Manski and Lerman (1977) proposed the weighted exogenous sampling maximum likelihood estimator (WESLM) which maximises

$$S = \sum_{i=1}^{n} w(j_i)\ \log P(j_i|x_i,\beta) \tag{5}$$

where the $w(j_i) = Q(j_i|\beta)H(j)^{-1}$ are known positive weights

Although less efficient than estimators proposed subsequently by Cosslett (1981), the WESMLestimatorhas the significant advantage of computational simplicity and was chosen on these grounds.

As H(j) is chosen by the researcher, it can be chosen to increase the efficiency of the WESML estimator. Amemiya (1985) and Cosslett (1981) have argued that under choice based sampling choice of H(j) equal to Q(j) (ie. choice of H(j) to replicate random exogenous sampling) is not necessarily the best sampling rule. For a binary logit model with one exogenous variable they showedfor a range of values for f(x) and Q(1), the most efficient choice of H(1) was H(1) = 0.5 ie. equal shares of positive and zero observations on the dependent variable. (Efficiency was defined as the minimisation of the ratio of the asymptotic variance under the sampling scheme H(1) to the variance under random sampling). Accordingly sampling rates for the two groups (families with cover, families without) were set to achieve a sample with H(1) as close as possible to 0.5. The final achieved sample size was 1026 family units, of which 464 were insured and 562 were uninsured.

The socio-economic nature of the data and the choice of the family as the unit of analysis meant collinearity between some of the independent variables was likely. Prior to the econometric analysis of the decision to purchase insurance, the data were tested for intra-spouse (association between different variables for one family member) and inter-spouse (association in measures of the same variables between spouses in one family) association or correlation. Significant, at $p<0.05$, intra- and inter-spouse association was found in the health ratings, attitudes to smoking and drinking, and different measures of income. Intra-spouse association was significant and positive in measures of recent medical care utilisation; inter-spouse association was significant and positive in occupation. None of these associations were surprising, but to overcome problems of collinearity and to reduce the size of the independent data set all independent variables were grouped into 3 sets, relating to income and employment, health, and demographic characteristics of all family members. A preliminary logit analysis of the decision to purchase was undertaken separately with each set of variables and in general, only those variables which significantly improved the goodness of fit of the model, as tested by the likelihood ratio (LR) test, were retained for further analysis.

3. **ECONOMETRIC ESTIMATES**

3.1 Model Selection Process

The aim was to select a small set of models which best explained the pattern of health insurance in the 1982 GHS. McCullagh and Nelder (1983) have stressed that one single model is not likely to dominate all others on all the criteria used to select the models and a single model should be viewed as one of a set of models which have a similar fit. Selection of models was made on the basis of theoretical validity, goodness of fit tests appropriate to qualitative models and log likelihood ratio (LR) and Lagrange Multiplier (LM) tests for specification error in logit models (Davidson and MacKinnon, 1984). The goodness of fit tests used are the pseudo R-squared defined by McFadden (1974) and the percentage of outcomes that are correctly predicted by the model (Judge et al, 1982). The qualitative nature of the independent variables meant some types of specification tests suggested for qualitative dependent variable models were of limited use; for example the use of simple plots of standardised residuals to detect omitted variables (Chesher and Irish, 1984) assumes normality.

The set of independent variables used in model estimation was large, as the decision to purchase was hypothesised to depend upon the income, employment and health of the spouse as well as head of the family. One version of the model is presented in Table 1 (referred to as Model 1). The sign and magnitude of the parameter estimates are similar to those derived using both larger and smaller sets of the regressors. While certain parameter estimates are not well defined, choice of variables in the independent variable matrix was made on the basis of the LR and LM tests, rather than on the significance of point estimates. The pattern of coefficient estimates in Table 1 indicates a positive association between purchase and income, employment of both spouses, and location in the South East and a negative association between purchase and various measures of health, medical care utilisation and smoking. The implications of these results will be discussed in more detail below; at this point we concentrate upon the process of model selection.

As income was hypothesised to be an important determinant of purchase, several different specifications of the income variable were tested (Table

2). Two income variables are used in Model 1; total family earned income and total family unearned income excluding social security payments. (The unearned variable, while not a measure of wealth, is perhaps best interpreted as an indicator of liquidity). Model 1 was re-estimated without the constraint that the coefficient on earned and unearned income of the two spouses (where present) be equal (Model 2). While the predictive power of the model improved slightly, the likelihood ratio test indicated that the fit of Model 2 was not significantly better fit than that of Model 1. Model 1 was re-estimated replacing family earned income with earned income per hour for the head of family (earnings for spouse were omitted on the basis of insignificant coefficients in Model 2). As Models 1 and 3 are not nested, an LR test was not used to choose between the two. Although the pattern of coefficient estimates is similar, the pseudo R-squared and predictive power of Model 3 is slightly poorer than that of Model 1. Finally, Model 1 was re-estimated under the hypothesis that the parameters on unearned and unearned family income are equal. This hypothesis (Model 4) was clearly rejected by the data.

Davidson and MacKinnon (1984) have proposed several computationally convenient Lagrange Multiplier tests for omission of specified variables and heteroskedacticity of known form in binary logit and probit models. Among the tests they discuss are three asymptotically equivalent tests based on the artificial regression of the standardised residuals

$$r_i(\hat{\beta};y_i) = [y_i-(1-F_i(\hat{\beta}))]/[F_i(\hat{\beta})(1-F_i(\hat{\beta}))]^{\frac{1}{2}} \tag{6}$$

upon the matrix $R(\hat{\beta})$ with typical element

$$R_{is}(\hat{\beta}) = [F(x_i(\hat{\beta}))F(-x_i(\hat{\beta}))]^{-\frac{1}{2}}\ f(x_i(\hat{\beta}))X_{is}(\hat{\beta}) \tag{7}$$

where $F(x_i(\beta)) = \exp(x_i(\beta))/(1+\exp(x_i(\beta)))$ in the logit model, $f(z)$ denotes the first derivative of $F(z)$, x_i is a row vector of exogenous variables individual i, β is a column vector of parameters estimated under the null hypothesis and $X_{is}(\beta)$ is the derivative of $x_i(\beta)$ with respect to β_s.

The regression of (6) upon (7) ie:

$$r(\hat{\beta}) = R(\hat{\beta})c + \text{errors} \tag{8}$$

generates three test statistics - the explained sum of squares from (8), denoted LM^2, n times the uncentered R^2 from (8) and a pseudo F - statistic,

$$F_2 = ((r'r-SSR)/k)\ (SSR/(n-m))$$

where r'r is the total sum of squares from (8), SSR the residual sum of squares from (8), k the number of restrictions, m the dimension of x_i, and n the number of observations. If there is only one restriction, the t-statistic on the column of R corresponding to the restriction is an asymptotically valid test statistic (Davidson and MacKinnan, 1984).

The specification of $x_i(\beta)$ as non linear allows these statistics to be used to test for heteroskedasticity of a known form. While the advantage of these tests over LR tests is small when testing for single omitted variables, the LM test for heteroskedasticity is considerably simpler than an LR test. Using LR tests, we sought to test the null hypothesis (Model 1) against the following hypotheses:

(i) Significant coefficient for age of head

(ii) Significant coefficient for higher order terms in both earned and unearned income

and using LM terms we tested the null (Model 1) against the hypothesis of heteroskedasticity in subsets of the regressors. The number of regressors in Model 1 prevented us from testing for heteroskedasticity in all regressors simultaneously. At the risk of omitted variable bias in the vector of variables causing heterskedasticity, we classified the regressors into three groups, (a) income variables, (b) health, health utilisation and smoking and (c) all other regressors in Model 1, and tested for heteroskedasticity in each of the three sets separately.

To avoid problems associated with the use of Davidson and Mackinnon LM tests under choice based sampling, all LM tests were carried out using a 10% random sample of the 1982 GHS. The number of purchasers in a 10% sample is small and under the null hypothesis (Model 1) the standardised residuals of all observations, and particularly those with positive insurance purchase, are rather large. The result is that the total sum of squares in the artificial regression, of the form of equation (8), is very large and in turn, the explained sum of squares is also large, though small in comparison with the total sum of squares. The explained sum of squares is the LM_2 statistic. In the tests of all three hypotheses above, the LM_2 statistic exceeded the critical value of X^2, so indicating rejection of the null. However, the other LM statistics (nR^2 and the F - statistic) indicated that it was not possible to reject the null of no heteroskedasticity in the specified form.

To further investigate these conflicting results we calculated the Lagrange Multiplier statistics as a test for the same omitted variables for which we had calculated LR tests. Monte Carlo evidence presented by Davidson and McKinnan (1984) indicated that the LM_2 test statistic rejected a true null less often than either the pseudo-LM statistics nR^2 or F_2 and less often than the LR test statistic. However, this pattern was not repeated for the present reasonably large data set. LR, nR^2 and F_2 statistics for omitted variables were less than the 95% critical value, while the LM_2 statistic indicated that the null should be rejected. We can only surmise that the poor performance of the LM_2 statistic compared to the LR test statistic is due to the large magnitude of some of the standardised residuals.

One further test of Model 1 is to compare the WESML point estimates with those of the non weighted 10% sample. The results for the 10% sample are presented in Table 3. The signs and magnitudes of the point estimates are similar to those of Model 1; the larger intercept perhaps indicates the lower information available on the purchasers of health insurance in the random sample.

These results do not mean that there are not omitted variables in Model 1 or that there is no heteroskedasticity, but imply that Model 1 cannot be rejected on the basis of either omitted variables or heteroskedasticity of the form specified above. In the absence of any theoretical grounds for expecting other variables in the data set to have significant coefficients or specifying other forms of heteroskedasticity, no further tests were carried out.

3.2 Estimation Results

In general, the results of the econometric analysis give some support to the hypotheses that insurance purchase is affected by value of time and expected health. In addition, the magnitude of almost all parameter estimates remain stable across different specifications of the matrix of exogenous variables and different data sets (the choice based sample, the random sample, the choice based sample excluding single person families and the choice based sample including families with heads over 64 years old (not presented here)). Although the R-square of the model is not high, this is neither uncommon in cross-sectional analyses nor unexpected in this data set given the discrete nature of many of the exogenous variables. Lack of data on variables such as political attitudes or demanders' knowledge of the quality of care in the two health care sectors would also have contributed to a reduction in explanatory power.

The results give support to the hypotheses that the probability of purchase is affected by income, and perhaps, by inference, the value of time, by health ratings and health utilisation, and perhaps also by attitudes to risk, and that the appropriate decision making unit is the family, rather than the individual.

3.2.1 Income and the Value of Time

Economic theory hypothesises that the value of time is a positive function of both income and the extent to which an individual/family is able to reallocate their uses of time. We would therefore expect positive coefficients on income variables, unearned income to have a smaller coefficient than earned income and positive coefficients on factors representing constraints on the decision making unit's ability to reallocate time. The estimated models (for example, Model 1) support these expectations. The income variables are of the expected signs (though the unearned income coefficient is not significant) and the impact of time constraints is supported by the positive coefficient on employment of head, employment of spouse, and overtime of head (though this is not significant).

A priori we would expect the presence of children to impose further constaints on allocation of time and here have a positive coefficient. In fact the coefficient for the variable 'number of children under 18', although not significant at the 95% level, was negative when entered into Model 1 (results not shown). However, the larger the number of children the lower income per capita in a family, so the negative and insignificant coefficient may result because the 'number of children' has both a positive and a negative effect on the value of time.

The negative coefficient on overtime of spouse is somewhat surprising, as we would have expected this to be of the same sign as overtime of head. Also somewhat unexpectedly, the coefficient on self employment (of head) is negative (though not well defined). A priori, it was expected that the income of the self-employed would be more affected by the need to take time off work in the event of illness and hence health insurance would be more attractive to these individuals. However, the future stream of income of the self employed may be less certain than that of employees, so a self employed individual may be less likely to purchase a relatively expensive insurance policy than an employee with the same income, location and health. In addition, the self-employed may be less risk averse, and so if they valued private sector care would prefer to pay for it if and when needed, rather than take out insurance. The sign and magnitude of the coefficient would then be determined by the relative strength of these effects.

3.2.2 Health

The coefficients of self assessed health rating for both head and spouse were insignificant. While not unexpected given the crude nature of the variable, it is interesting to note that the parameter estimate for the spouse (always female) is larger than that for the head. This pattern was repeated in the medical care utilisation variables. This pattern does not appear to result from intra-spouse collinearity. It may indicate that the health of dependents is a more important factor in determining purchase than the health of the purchaser, or, more speculatively, that the health of women is a more important determinant of insurance purchase than the health of men (all spouses are women in the GHS sample, but not all heads are men). The insignificant sign of any variables relating to the health of children may be a reflection of the nature of the treatments covered by health insurance and relative benefits of the private and public sectors for particular types of treatment. First, if the illnesses children are most likely to get are not covered by insurance, the health of children will not have any direct positive effect on the probability of health insurance purchase. Second, if public sector treatment for children is viewed as no worse or better than private sector treatment then again there is no benefit from the purchase of health insurance to cover children.

The negative sign on outpatient utilisation (and on chronic illness of head) indicates that families with members with poorer health appear to be less likely to buy health insurance. This group may have a lower purchase rate because they fear that their health services utilisation record would mean higher premiums or even total exclusion from purchase of an insurance policy. This hypothesis may be supported by the negative (though insignificant) parameter estimates for current smoking for head and for spouse.

3.2.3 Risk Aversion and other factors

The sign of the coefficients on self employment and on smoking may be some evidence that the less risk averse are less likely to purchase health (as other) insurance. The variable which may act as a proxy for cost of access to private relative to public care, South-East, has an insignificant coefficient but is of the expected sign. A greater proportion of private facilities are located in this area than any other in the UK, so travel costs to private facilities are likely to be lower for those resident in the South-East.

4. EXTENSIONS TO CURRENT MODEL

Although the coefficient estimates are generally of the expected sign, several are not well defined. While the ranking of predicted probabilities from the model is fairly consistent with the observations, the model underpredicts the probability of purchase. It would appear that certain important determinants of purchase have been omitted from the econometric model. In part, these omissions may be the result of poor data, but they may also arise from some misspecification of the underlying theoretical model. Below we discuss possible extensions to the current model and indicate the impact omission of these factors could have on the estimation results. Subsequently, we outline the type of data than would seem to be required to test the proposed modifications to the theoretical model, and briefly discuss the work we are now carrying out to test these modifications.

The current model has two central assumptions:

(1) choice is made on the basis of expected utility of the two prospects in the next period; although the value and/or probability of future outcomes may be affected by past actions (for example, the probability distribution of future states of health may be a function of past states, expectations of quality of care may be a function of past utilisation of the health services) it is assumed that the decision at time is independent of all prior and subsequent decisions.

(2) individuals choose, at time t, between two prospects - the purchase or non-purchase of health insurance.

There are several reasons for believing one or both of these assumptions may not be appropriate for a proportion of decision makers.

4.1 The Role of Past and Future Decisions

(1) Past purchase or consumption has been found to be a determinant of current consumption in demand studies and may also play a role in the decision to purchase health insurance. The decision to buy health insurance requires the evaluation of several unknowns and so the costs of decision making may be relatively high. If so, individuals may not reconsider their decision until their circumstances change considerably. If circumstances change little in the period following the initial decision, the perceived costs of re-evaluation may be greater than the expected gains.

If decision makers do not alter their behaviour as the result of marginal changes in either endowments or the choices they face, we would expect past purchase to be an important determinant of present consumption, and the weights on all factors to be a function of the time elapsed since the initial decision was taken. Errors in optimisation due to habit may also lead to a non-symmetric distribution of difference in errors between the two choices. For example, let us assume two choices, A and B, and two groups of decision makers, 1 and 2. Let utility be defined as a random variable, and let group 1 make errors such that they overrate option A and group 2 make error such that they overrate option B. The distribution of the difference in errors, $g(e^A-e^B)$ will not be symmetric around mean = 0.5 for either group, but will be positively skewed for group 1 and negatively skewed for group 2. If the proportions of group 1 and group 2 individuals in the population is not equal, the distribution of errors in the population will be skewed.

Errors in optimisation may explain, in part, the pattern of predicted values in the sample. The proportion of the population purchasing health insurance in any one year is under 10%; if the errors in optimisation argument outlined above holds, we would expect a positively skewed distribution of errors in the population. Since the predicted values in a binary logit model are the errors deducted from a constant (0 or 1), we would expect the negatively skewed distribution of predicted values found for Model 1.

(2) Individuals may purchase health insurance at time t, less because they think they will need it in period t, but more because they think that unless they buy insurance at time t, they may be excluded from purchase at some later date. For example, no health insurance funds accept new subscribers over the age of 64.

Individuals who face restricted choice sets can only choose one of the two options. In the economics of transport literature this problem is referred to as 'captivity' to one of the possible choices. Swait and Ben-Akiva (1985) have shown theoretically that the effect of captivity to one option in a binary logit model is to bias parameter and variance-covariance estimates. If captivity is ignored, the estimated coefficients of all terms except the constant of the model may be downwardly biased and less significant than in the 'true' model.

Captivity in transport economics may be easy to establish; for example if commuters choose between public and private transit for the journey to work and a certain group live in communities with no public transit, this group are likely to be captive to private modes of transit. Captivity to one choice in the choice of health insurance is harder to establish; however, there are some groups in the population for whom the probability of captivity to non-insurance may be high. For example, individuals who do not consider the private sector as an option for political reasons, or those individuals excluded from purchase of health insurance because of age or past medical care utilisation may be captive to the choice of no insurance.

One possible method of overcoming the problems of captivity is to model the decision to purchase health insurance as a two stage probabilistic process. We assume there are only two choices, choices 1 and 2. Individuals can only be captive to choice 1. Choice 1 represents non insurance, choice 2 insurance.

Let p_i = probability individual i will not be captive to option 1.

Let F_i = probability individual i is not captive and chooses option 2.

The probability of choice of option 2 is therefore the product of the probability that the individual will not be captive and the probability he will choose option 2 if not captive. This probability is given as

$$= P_i F_i \tag{9}$$

and the probability of not choosing option 2 as

$$\begin{aligned} &= (1-P_i) + P_i(1-F_i) \\ &= 1 - P_i F_i \end{aligned} \tag{10}$$

The likelihood for this process is given as

$$L = \prod_{0} 1 - P_i F_i \prod_{+} P_i F_i \tag{11}$$

where the 0 denotes those individuals who are observed to have zero purchase of choice 2 and the + denotes those individuals who are observed to have positive purchase of choice 2.

(11) is essentially a 'double hurdle' model; estimation of (11) depends on the assumption made about the relationship between P_i and F_i. In an analysis of demand for household expenditures Deaton and Irish (1984) assume $p_i = p$ for all i. They also replace F_i with a density function since they have observations on the level of purchase. Gaudry and Dagenais (1979), in an analysis of transport choice, assume p_i varies across individuals, but is independent of factors affecting F_i. This led to the 'Dogit' model. Van de Ven and van Praag, in analysis of the demand fordeductibles in health insurance, assume P_i and F_i to be bivariately normally distributed.

Unfortunately, although the idea of captivity is perhaps a useful way of examining the demand for health insurance, we have neither detailed data on the choice process to support or refute the theoretical concept of captivity, nor the data to empirically test such a model of captivity. Several factors which may determine both the probability of captivity and the probability of choice, conditional on not being captive, are not measuredin the 1982 GHS. For example, there is no data on political attitutes. Nor do we have detailed data on medical history of potential demanders to establish whether they would be given only restricted cover or might view themselves as ineligible for cover.

We have therefore two options. The first is to examine the current data set for some evidence of the effects of captivity. For example, following Swait and Ben-Akiva (1985), we can search for evidence that the parameters are downwardly biased if captivity is ignored by identifying captive groups and re-estimating the model without these observations. The second is to explore the decision to purchase insurance using other data sources.

The first option requires that we can correctly identify the choices to which individuals may be captured and that we can exclude captured individuals from an analysis in order to estimate the model of choice conditional on no capture. For the purposes of an exporatory analysis we assumed

(i) the compulsory nature of public health insurance, and the nature of private insurance contracts meant 'capture' was possible only to the no-insurance choice,

(ii) the probability of capture was a function of low income (because insurance is a relatively expensive good).

We therefore stratified the sample by mean income. The results are presented in Table 4. A comparison of the coefficients in Table 1 and Table 4 indicates some support for the hypothesis that the low income group are more likley to be captured. The estimate of the coefficient of the constant in Model 1, which is estimated on the whole sample, is higher and the coefficients of most other variables lower than the estimation in Table 4 for the higher income group only.

These results are very preliminary. We currently have no data which will allow us to distinguish between individuals who are captive and those who see both choices as possible but have a very low probability of purchase of one of the choices. We have hypothesised that income might be a proxy for capture, but not all of those families with low income will view themselves as captive to the non-insured choice. Finally, even if income were a good proxy for a high probability of captivity to the no insurance choice, segmentation reduces the number of observations used to estimate the model, so decreasing the probability that the model will provide a good fit to the data.

4.2 Collection of Further Information

To test properly the hypothesis of the role of past decisions and the extent of restricted choice sets and captivity, it is necessary to have information on the choices individuals perceive as open to them, on the factors individuals take into consideration when they decide whether or not to purchase and on the time scale of their decision. It does not appear that this information is available in any British secondary data set. We therefore have initiated a project to collect this information.

From a pilot survey with a substantial qualitative component we have established some of the reasons why individuals purchase or do not purchase health insurance, some of the reasons why they would or would not consider purchase and some of the reasons why they might consider stopping purchase. These results have been used to design a questionnaire that seeks to get information on the choices individuals think they face, on the reasons for purchase and non purchase and on the time horizon for which purchase is made. The questionnaire is also designed to collect data on current health status, past utilisation of public and private medical facilities by the respondent and other members of the household and his/her social networks, attitudes to public and private medicine, education, employment status and income. In addition, the questionnaire includes the first UK attempt to establish a valuation of the costs to individuals of waiting lists for acute surgical treatment.

This data is to be collected from a nationally representative sample of individuals aged 25-70. The achieved sample is to be about 1,200 individuals. This research is not as a substitute for econometric analysis of secondary data but a complement and is designed to answer some of the questions raised by the econometric estimation and to further our understanding of the process of consumer choice of private health insurance and private health care.

Table 1 : Model 1 (Logit Estimates)

	Coefficient	Standard error
Constant	-3.896 **	1.027
Urban	-0.409	0.289
South-east	0.308	0.27
Spouse	0.218	0.471
Class 1 or 2	0.36	0.297
Head in work	1.683 **	0.647
Spouse in work	0.668 **	0.325
Self-employed head	-0.299	0.441
Overtime, head	0.352	0.363
Overtime, spouse	-0.935 **	0.463
Good health, head	-0.932 E-01	0.322
Good health, spouse	-0.477	0.307
Chronic illness, head	-0.260	0.303
Smoker, head	-0.244	0.265
Smoker, spouse	-0.439	0.308
Outpatient, spouse	-0.668 *	0.396
GP consultation, spouse	0.388	0.397
H'hold earned income	-1.079 **	0.361
(H'hold earned income)^2	0.204**	0.057
H'hold unearned income	-0.400 E-01	0.309
(H'hold unearned income)^2	0.115	0.081
Log - likelihood	-243.46	
Pseudo R^2	0.12	
% correctly predicted	56%	
n	1026	

** $p < 0.05$

Specification tests

(1) For heteroscedasticity in all health variables; LM2 = 192.5626 (14.067), nR^2 = 1.3848 (14.067)

(2) For heteroscedasticity in urban, south-east, spouse, cl12, number of children LM2 = 335.5 (11.07), nR^2 = 2.409 (11.07)

(3) For heteroscedasticity in all income variables; LM2 = 269.2 (9.488), nR^2 = 1.3041 (9.488).

LM2 and nR^2 are Davidson and MacKinnon (1984) tests. Critical values at 95% in brackets besides test statistics.

TABLE 2 :

LR Tests of Income Variables

(Logit estimates)

	Model 2		Model 3		Model 4	
	Income of spouses separately		Earned income/hr		Total income	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
Constant	-3.98 **	1.03	-4.35**	0.987	-4.27. **	1.445
Urban	-0.456	0.289	-0.44	0.288	-0.42	0.284
South-East	0.25	0.27	0.36	0.265	0.306	0.267
Spouse (dummy)	0.18	0.50	0.28	0.47	0.208	0.457
Class 1 or 2	0.327	0.29	0.45	0.286	0.449	0.288
Head in work	1.45 **	0.666	0.79	0.37	0.006	0.460
Spouse in work	0.65	0.549	0.82 **	0.325	0.4768	0.315
Self-employed, head	-0.456	0.449	-0.17	0.43	0.006	0.430
Overtime, head	0.308	0.366	0.296	0.367	0.355	0.36
Overtime, spouse	-1.04 **	0.48	-0.74	0.485	-0.619	0.492
Good health, head	0.031	0.325	0.0019	0.32	-0.124	0.308
Good health, spouse	-0.508 *	0.309	-0.515*	0.306	-0.439	0.305
Chronic illness, head	-0.2336	0.305	-0.229	0.306	-0.187	0.302
Smoker, head	-0.1947	0.267	-0.248	0.26	-0.284	0.263
Smoker, spouse	-0.518 *	0.306	-0.425	0.31	-0.504*	0.304
Outpatient , spouse	-0.618	0.39	-0.58	0.39	-0.405	0.408
GP consultation, spouse	0.3187	0.399	0.38	-	0.326	0.387
Earned income, head	-0.96	0.35	-	-	-	-
(Earned income, head)^2	0.20 **	0.066	-	-	-	-
Earned income, spouse	-0.245	0.34	-	-	-	-
(Earned income, spouse)^2	0.079	0.065	-	-	-	-
Earned income/hour	-	-	0. 586**	0.224	-	-
(Earned income/hour)^2	-	-	0.046**	0.018	-	-
Unearned income, head	0.0089	0.366	-	-	-	-
(Unearned income, head)^2	0.06	0.09	-	-	-	-
Unearned income, spouse	-0.408	0.586	-	-	-	-
(Unearned income, spouse)^2	0.295	0.219	-	-	-	-
H/hold unearned income	-	-	0.02	0.309	-	-
(H/hold unearned income)^2	-	-	0.095	0.08	-	-
Total income	-	-	-	-	-0.03	0.590
(Total income)^2	-	-	-	-	0.087	0.0775
Log-likelihood	-242.62		-243.94		-249.41	
R^2	0.12		0.11		0.10	
% correctly predicted	57%		55%		55%	
n	1026		1005		1026	

* $p < 0.10$

** $p < 0.05$

Table 3 : Model 1 re-estimated using 10% random sample.

(Logit Estimates)

	Coefficient	Standard Error
Constant	-4.411 **	1.023
Urban	-0.468	0.322
South East	0.408	0.304
Spouse	0.8937	0.556
Class 1 or 2	0.196	0.367
Head in Work	1.911 **	0.8618
Spouse in work	0.436	0.361
Self employed, head	-1.1168 *	0.666
Overtime, head	0.8758 **	0.411
Overtime, spouse	-0.7989	0.657
Good health, head	-0.2058	0.383
Good health, spouse	-0.14247	0.363
Chronic illness, head	-0.195	0.367
Smoker, head	0.197	0.3066
Smoker, Spouse	-0.207	0.348
Outpatient, spouse	-1.154 *	0.602
GP visit, spouse	0.444	0.415
Earned income	-1.146 **	0.457
$(\text{Earned income})^2$	0.18245 **	0.737 E-01
Unearned income	-0.393	0.377
$(\text{unearned income})^2$	0.160	0.100
log-likelihood	-170.51	
Pseudo R^2	.13	
% Correctly predicted	91%	
n	621	

* $p < 0.10$
** $p < 0.05$

able 4: Segmentation by Mean Income

(Logit Estimates)

	Household Income Above Mean Income for Sample		Household Income Below Mean Income for Sample	
	Coefficent	asymptotic t - ratios	Coefficent	asymptotic t-ratios
onst.	-2.52	(-1.056)	-4.32	(-2.41)
rban	-0.458	(-1.14)	-0.234	(-0.45)
outh-East	0.4217	(1.159)	0.0235	(0.047)
pouse	0.065	(0.08)	0.2081	(0.23)
lass 1 or 2	0.227	(0.568)	0.4739	(0.88)
ead in Work	1.555	(0.995)	1.960	(2.52)
pouse in Work	0.602	(1.34)	0.844	(1.36)
ead, Self-Employed	-0.317	(-0.45)	-0.475	(-0.71)
vertime, Head	0.426	(0.94)	0.3115	(0.29)
vertime, Spouse	-0.87	(-1.51)	-0.563	(-0.344)
ood Health, Head	-0.31	(-0.65)	0.195	(0.368)
ood Health, Spouse	-0.54	(-1.33)	-0.44	(-0.648)
hronic Illness, Head	-0.32	(-0.76)	-0.108	(-0.186)
moker, Head	-0.097	(-0.27)	-0.436	(-0.893)
moker, Spouse	-0.53	(-1.37)	-0.364	(-0.483)
utpatient, Spouse	-0.652	(-1.25)	-0.536	(-0.567)
.P. Consultation, Spouse	0.448	(0.8)	0.255	(0.32)
arned Income	-1.44	(-1.46)	-0.87	(-1.367)
Earned Income)^2	0.248	(2.07)	0.147	(1.12)
nearned Income	-0.049	(-0.11)	0.017	(-0.024)
Unearned Income)^2	0.093	(0.708)	0.135	(0.80)
og-Likelihood	-197.67		-66.64	
seudo R^2	0.08		0.10	
of sample	33.6		66.4	
m 2	301.1325 (9.488)		9.484 (9.488)	
m 1	3.227 (9.488)		0.020 (9.488)	

Lm2 is Davidson and McKinnon (1984) LM2 test for heteroscedasticity with respect to all income variables jointly. lm1 is Davidson and McKinnon (1984) nR2 test. Critical values at 95% in brackets besides test statistics.

ll income variables are gross [illegible] measures.

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APPENDIX

In an extensive analysis of choice between two certain alternatives, McFadden(1974,1975,1981) has shown that the econometric estimation of discrete choice between certain alternatives has a foundation in utility maximisation if utility is specified as a random function which is additively separable in a deterministic and a random component. Further, under certain specifications of the form and distribution of the error component this model of utility maximisation can be estimated by either probit or logit statistical models.

Although it has been shown that decision makers make errors in assessment of choice under uncertainty, the appropriate way to model this randomness is as yet unresolved (Machina, 1983). One possible approach is to try to apply the idea of random utility as defined by McFadden to choice under uncertainty between two or more discrete alternatives. However, the extensions of random utility to choice under uncertainty is less than straightforward. In this brief note, we outline McFadden's argument and then attempt to extend the specification of randomness to choice under uncertainty. We basically attempt to introduce some notion of randomness into an expected utility framework. We show that only if the error process is assumed to have a particularly simple, and perhaps not very plausible form, can the coefficients from the statistical model be interpreted as in the McFadden model ie. as the parameters of the deterministic component of utility.

A.1.1. Random Utility Model

McFadden assumed utility is a random function of the form

$$U(x^j,s) = V(x^j,s)+e(x^j,s) \tag{A1}$$

where $U_j(.)$ is the random utility derived from the jth choice, $V_j(.)$ is the deterministic component and reflects the 'representative' tastes of the population and $j(.)$ is stochastic and reflects the effect of individual idiosyncracies in taste, errors in judgement and/or errors of measurement by the analyst. The arguments of the utility function $V_j(.)$ are the attributes of the choice, x^j and the socio-economic characteristics of the choice maker, s (fixed across options for each choice maker).

The individual will choose the option which maximises random utility; since utility is stochastic, the event that an individual will choose option i is stochastic and will occur with some probability P_i, written as

$$P_i = \Pr[U(x^i,s)>U(x^j,s) \text{ for } j \neq i, j = 1, \ldots, J] \tag{A2}$$

For simplicity of exposition let $U(x^j,s)=U^j$, $V(x^j,s)=V^j$ and $e(x^i,s)=e^j$.

Substituting (A1) into (A2) and rearranging

$$P_i = \Pr[e^j-e^i)<(V^i-V^j) \text{ for } j \neq i, j = 1, \ldots, J] \tag{A3}$$

The choice of estimator depends on the specification of the probability distribution of U^j and so (e^j-e^i). It is assumed the e^j are i.i.d. and independent of any of the factors which determine V^j.

Two probability distributions for (e^j-e^i) are commonly assumed, the logistic and the normal, which result in the estimation of the logit and probit models respectively. The two models are virtually indistinguishable except at arguments yielding probabilities close to zero or one, where the probit model approaches the extreme values more rapidly.

If the deterministic component $V(x^j,s)$ can be specified in the general linear form,

$$V(x^j,s) = Z(x^j,s)'\beta \tag{A4}$$

where the $Z(x^j,s)$ are known functions of the attributes of the choices and socio-economic characteristics of the choosers and β is a vector of unknown parameters, the β s have the simple interpretion of the weights attached to the Z(.) functions in the calculation of utility. These weights are implicitly the same in all states of the world. In an estimation of a logit model where the dependent variable is 1 if the individual is observed to choose option i, 0 otherwise, β_k is the estimate of the effects of a unit change in Z^k on the log of the odds ratio $P_i/(1-P_i)$.

A.1.2. Choice under uncertainty

The widely used expected utility theory of choice under uncertainty argues that expected utility of option i, EU^i is given as

$$EU^i = \Sigma_t \; p_t U^i_t \tag{A5}$$

where i indexes the choice, t the state and

U^i_t = utility of i in state t

p_t = (subjective) probability of state t occuring

$\sum_t p_t = 1$

Expected utility theory does not permit error on the part of the decision maker. To estimate a statistical model of choice between prospect i and prospect j when expected utility is defined as in equation (A5) requires an assumption of errors in measurement by the observer. The problem of this approach for discrete choice is that errors in measurement must account for movement between non-choice and choice of option i, rather than intramarginal changes in the amount of a good consumed. In addition, there is a growing body of literature (for a review see Machina, 1983) which indicates individuals do make errors of judgement in situations of choice between uncertain prospects. However, although there is evidence of behaviour which violates expected utility maximisation, there is no general consensus as to the nature of the error process.

If error can be modelled as entering only the calculation of the utility of a choice i in state t and not into the assessment of the probability that state t occurs, then the expected utility framework can perhaps be extended to incorporate random utility as modelled by McFadden. An extension that is perhaps most in keeping with McFadden is to respecify the utility of choice i in state t as stochastic, of the form

$$U_t^i = V_t^i + e_t^i \tag{A6}$$

where $V^i{}_t$ is a deterministic component and e_t^i a random component, assumed independent of $V^i{}_t$.

Substituting equation (A6) into (A5) the 'random' expected utility of choice i is

$$EU^i = \sum_t p_t \; (V_t^i + e_t^i) \tag{A7}$$

and substituting this definition of expected utility into (A2) and rearranging the probability an individual will choose i rather than j is

$$P_i = \Pr\,[\Sigma p_t (e_t^j - e_t^i) < \Sigma p_t (V_t^i - V_t^j) \text{ for } j \neq i,\ j = 1,\ \ldots,\ J] \tag{A8}$$

The differences between the errors and the differences between the deterministic components are now state weighted differences. If the deterministic component of utility of choice i in state t is specified as in equation (A4) as a linear combination of known attributes of choice and decision maker but allowing the level of these attributes to vary across states, the deterministic component of utility for choice i in state t is given as

$$V_t^i = Z(x_t^i, s)' \underline{\beta}_t \qquad \text{(A9)}$$

Substituting (A9) into (A8) and rearranging the probability of choice of prospect i becomes

$$P_i = \Pr[\Sigma p_t (e_t^j - e_t^i) < \Sigma p_t \beta_t (Z_t^i - Z_t^j) \text{ for } j \neq i,\ j = 1, \ldots, J] \qquad \text{(A10)}$$

From equation (A10) it is clear that the parameter of coefficients derived in either a logit or probit model can only be related to the weights attached to each, of the attributes of the choice if the weights are state independent ie. $\beta_t^k = \beta^k$, $k=1, \ldots, J$. This in turn implies state independent utility functions.

The above discussion perhaps indicates that either fairly implausible assumptions about the nature of error made by the observer or fairly restrictive forms of the process of utility formation under uncertainty have to be adopted in order to link the choice process closely to a simple probit or logit model.