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Derivation of a Needs Based Capitation Formula for Allocating Prescribing Budgets

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Derivation of a needs based capitation formula for allocating prescribing budgets.

Results of a study commissioned from the University of York by the National Health Service Management Executive

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Preface

This document reports the results of a study commissioned by the NHS Executive to examine the determinants of NHS practice level prescribing expenditures. The purpose was to develop a needs based capitation formula for allocating annually approximately £4.5 billion of NHS revenues to Health Authorities and thence Primary Care Groups in England. The work was reported to the Advisory Committee on Resource Allocation and their technical advisory sub-group, TAG. The methods and modelling were therefore subject to a great deal of scrutiny with various sensitivity tests and alternative model specifications being proposed at almost every stage. This has resulted in the development of a robust model, but also explains some of the "stop-go" nature of the analysis reported in the text. The report sets out the background to the study, describes the data on which it is based, explains the statistical methodology used, and presents the findings. The implications for revenue allocations to Primary Care Groups are not discussed in this report.

Acknowledgements

The work presented in this report was commissioned by the NHS Executive and reported to the Advisory Committee on Resource Allocation (ACRA) their technical advisory sub-group (TAG) at various stages of completion. We are grateful for comments on the work presented and suggestions of further analyses received from both these groups. Much of the motivation and impetus for this work was provided by Keith Derbyshire of the NHS Executive and we wish to acknowledge the effort and guidance received from him. We are also grateful to Roy Carr-Hill and Peter Smith, University of York, for constructive comments throughout.

1. Introduction

1.1 The purpose of this research report is to present findings of a statistical analysis of the population needs based determinants of practice level prescribing expenditures using data on practice level characteristics together with small area data attributed to practice populations. The study was commissioned by the NHS Executive and conducted at the Centre for Health Economics, University of York, with the support of the Prescribing Support Unit, Leeds.

1.2 The publication of the White Paper; The New NHS; Modern, Dependable (Department of Health, 1997) proposing the creation of Primary Care Groups with responsibilities to meet the health care needs of their populations within an annual budget, together with the Government's commitment to provide health care services on an equitable basis has highlighted the need to define practice budgets on a rationale basis and to link expenditure to population health care needs.

1.3 For Hospital and Community Health Services expenditure mechanisms already exist for allocating monies from central Government to Health Authorities and thence to fundholding practices (Carr-Hill et. al. 1994). Such mechanisms will be sufficient for the purpose of allocating to Primary Care Groups. For prescribing expenditures, although presently a formula for allocating monies to Health Authorities on the basis of population need exists, the suitability of this formula to devolve budgets from Health Authorities to Primary Care Groups or indeed individual practices has not been evaluated.

1.4 This report presents the results of a study aimed at examining the determinants of practice level prescribing expenditures by relating costs to population needs. Section 2 contextualises the problem by describing past and present mechanisms for allocating monies to practices; Section 3 outlines the methods and assumptions used throughout this work; Section 4, describes the data used and how this was attributed to individual practice populations, whilst Section 5 operationalises the methods by describing the statistical modelling procedures adopted. Results and conclusions are presented in Sections 6 and 7 respectively.

1.5 The implications and possible consequences for Primary Care Groups of being held responsible for budgetary control is beyond the scope of this report; the interested reader is referred to Smith (1999) for a discussion.

2. Resource allocation and prescribing

2.1. Allocations for prescribing expenditures have, until recently, been largely based on historical costs adjusted for inflation and the demographic structure of populations, but with no additional adjustment made to address differences in population need. More recently, allocations to Health Authorities have moved towards a weighted capitation system in response to an emphasis within the NHS to promote equity of access to health care. Accordingly, in 1996/97, for the first time, a proportion of the prescribing budget was based on a needs weighting. After appropriate adjustments for the age, sex and temporary resident characteristics of practices using what are termed Age, Sex and Temporary Resident Originating Prescribing Units (ASTRO-PUs, Roberts and Harris, 1993), a weighting for the proportion of people in the 1991 Census declaring themselves as unable to work due to permanent sickness or disability was applied to calculate Health Authority allocations (Rice et. al., 1997). Total prescribing costs in 1996/97 accounted for £3.8 billion; 14% of all local NHS expenditure.

2.2. The methodology for devolving Health Authority prescribing budgets to individual general practices is much less advanced. This is somewhat surprising since fundholding GPs have for some time been required to manage prescribing budgets and to maintain spend within a capped limit. Indeed, the creation of fundholding was intended, in part, to place much greater emphasis on cost-effective prescribing in an attempt to control the rise in total prescribing costs and evidence suggests that this has, in part, been achieved (Department of Health 1994). Non-fundholders have enjoyed much greater flexibility in that they have been required to contain prescribing spend within an indicative budget. However, the lack of incentives or punitive measures to encourage compliance on the part of the GP has lead to criticism of the scheme which has generally failed to control the rise in costs (Walley, Wilson and Bligh, 1995).

2.3. Hitherto, guidance issued to Health Authorities from the NHS Executive on setting primary care prescribing budgets has used, as a starting point, previous years spend. From this basis, HAs have been required to consider an uplift plus growth factor for practices whose budget share, adjusted for the demographics of practice lists and other need factors, is below the local average (NHS Executive 1997). Through this mechanism, adjustments for population 'need' are incorporated into the budget setting process to promote the distribution of monies on a more equitable basis.

2.4. The predominant determinant of this process, aside from previous years spend, is the adjustment for practice demographics. This is achieved through the use of practice ASTRO-PUs (age-sex and temporary resident originated prescribing units) (Roberts and Harris (1993) and Lloyd, Roberts and Sleator (1997)). ASTRO-PUs provide weights applied to practice lists to reflect the prescribing costs of different age and gender groups. Their use is intended to capture the differential demands placed on practice prescribing through different demographic compositions of practice populations.

2.5. However, whilst this method of capitation accounts for a reasonable proportion of variation observed in prescribing costs across practices (approximately 25%) (Roberts and Harris, p488, 1993), there are wide variations between Health Authorities and practices and various possible correlates of these have been proposed; for example, out-of hours services and prescription charge exemptions (Whynes, Baines et. al., 1996), and the concentration of nursing homes and residential homes in some Health Authorities. In an attempt to incorporate such factors in the budgetary procedures, initial budgets based on ASTRO-PUs are subject to bilateral negotiation between practices and Health Authorities to ensure that any special needs a practice may encounter are met. However, this procedure may give rise to incentives for strategic behaviour and inequity, in the sense that allocations are not related to a consistent concept of need.

2.6. The publication of the White Paper, *The new NHS; Modern, Dependable* (Department of Health, 1997) advocating the creation of Primary Care Groups has accelerated the need for defining practice level budgets on a more equitable basis, systematically related to need. Paragraph 5.17 states "Each Primary Care Group will have available their population's share of the available resources for hospital and community health services, prescribing and general practice infrastructure. These resources will allow the Group and its members to commission and provide services. Within this single cash limited envelope, the Group will have the opportunity to deploy resources and savings to strengthen local services and ensure that patterns of care best reflect their patients' needs." The exact definition of 'population share' is unclear, but, in order to promote equity of access to health care it must encompass some concept of population need.

2.7. To date, little empirical research has been performed to investigate the feasibility of deriving a needs based formula for distributing prescribing funds at practices level.[1] Current models at the Health Authority level include the use of permanent sickness to adjust age and gender weighted populations, but the reliability and use of this variable at the practice level has not been the subject of investigation.

2.8. This report presents findings of a study to investigate the feasibility of deriving a practice level prescribing formula based on the well rehearsed procedure of relating measures of population need to current utilisation. Much of this work, particularly the methodology adopted, has been set out and described in great detail in the York study which developed the formula for distributing NHS revenues to HCHS (Carr-Hill et. al. 1994). The reader is referred to this work for a thorough grounding in the assumptions on which this study is based

3. Methods

3.1. *Equity in the allocation of resources*

3.1. The founding principles of the NHS included the notion of equality of access for those in equal need. This principle remains intact today, and forms the motivation for this study. However, although some concept of equity underlies any attempt to allocate resources rationally, the analysis of various notions of equity is notoriously complex (for example, see Pereira (1993) and Mooney (1982)).

3.2. The criterion of equity adopted here corresponds to what has become the pioneering work in resource allocation methodology, namely the English formula for allocating HCHS monies (Department of Health and Social Security, 1976), of equity of input for equal need. The models developed describe the impact of health

[1] An exception to this is Hancock (1997), who has developed an indicative prescribing formula to allocate budgets to GPs throughout Scotland.

and social needs on resource utilization after adjusting for supply factors. However, it is noted that this was performed in isolation from the provision of other social welfare services and it could be argued that the demand for general practice services such as prescriptions are not independent of the provision of other public services such as secondary care, personal social services and public sector housing. The integration of other social welfare services is beyond the scope of this study.

3.3. The general approach is in line with society's requirements of the NHS in that the principle of populations in equal "need" receiving equal resource allocations is paramount. Underlying the methods is the notion that the benchmark for need is the existing use of resources at the national level by particular age/gender population groups. Local allocations are then adjusted appropriately for their local demographic structure which in turn may then be adjusted again according to local population health care needs. Defining appropriate adjustments for this latter component forms the thrust of this report.

3.2. ***Demand for health care***

3.4. The demand for health care is a complex process, but in order to proceed the following schematic representation is offered. Figure 1 illustrates the major components in the demand for health care capturing the salient features required for the ensuing utilisation based analysis.

3.5. Underlying socio-economic and demographic characteristics of populations give rise to health care needs, in terms of morbidity. This, in turn, gives rise through some imperfectly understood process to the demand for health care services. However, other socio-economic characteristics, such as social needs and expectations independently influence demand over and above those operating through health needs.

3.6. Other factors influencing the demand for health care include the local supply of other health related services and wider social services. For example, when a general practitioner decides to refer a patient to a consultant, this decision may be influenced by expected waiting times which will be a function of availability of beds. This may impact on the supply of prescriptions to patients on waiting lists (longer waiting times may result in longer periods of repeat prescriptions). The general management of patients may also be seen as being influenced by availability of other general practitioner services in the local area through competitive processes (Scott and Shields (1997)). In addition, there is a body of research which suggests that "supplier-induced demand", or indeed "supplier-suppressed demand" might be an important consideration in the demand for health care (Cromwell and Mitchell, 1986). These all indicate that surrounding supply conditions are important in understanding the demand for health care services.

3.7. In general practice, the adopted style of practice can be assumed to have a significant impact on the costs of prescribing. More innovative and better informed practices actively encouraging cost effective prescribing will usually be cheaper per capita for a given level of need. It may be hypothesised that such practices are more likely to be those who are fundholding and/or training practices where incentives exist to prescribe in more innovative ways.

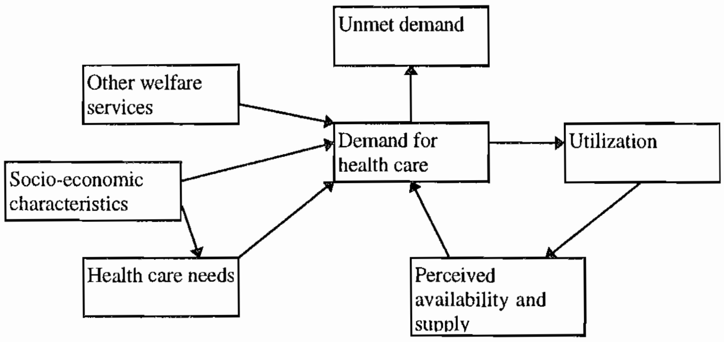

Figure 1: A schematic representation of the demand for health care

3.8. The underlying need for health care, augmented by social circumstances and expectations generate a demand for health care. In the light of this demand and the local political process, NHS services are provided. However, the adequacy of local supply in meeting this demand will affect future expectations and thence future demand. This, in turn, affects the future supply of health care. By this process a feedback loop from supply to demand is created defining the actual use of NHS facilities as a dynamic process with lags between the many of the links in figure one.

3.9. Modelling such a dynamic process is complex and requires time series data if the underlying links are to be exposed in detail. For cross-sectional data a simplified model of this process can be represented algebraically. Let U represent our measure of utilization, N a measure of health care needs, X wider socio-economic characteristics and S supply; then utilization can be assumed to be a function of health care needs and supply in the following manner:

$$U = f(N, S) \qquad (1)$$

3.10. Health care needs in equation (1) are a function of wider socio-economic and demographic conditions:

$$N = f(X) \qquad (2)$$

3.11. The supply of health care is itself a function of utilization (past and present), health care needs and wider socio-economic circumstances:

$$S = f(U, N, X) \qquad (3)$$

3.12. The system of equations (1) to (3) indicate that utilization and supply are determined simultaneously. This creates difficulties for standard approaches to regression analyses. In the absence of the feedback loop between supply and utilization, equations (1) and (2) could be estimated in a straight forward manner using ordinary least squares, since both needs and supply would be assumed to have an exogenous impact on utilization. However, systems of equations described by (1) to (3) are termed endogenous and require highly technical statistical methods to solve. The use of ordinary least squares would produce biased coefficients which do not reflect properly the real impact a needs variable could be expected to have on utilization. A technical account of the regression models used to account for endogeneity of the kind described is provided as Appendix I.

3.13. Although in theory endogeneity of supply may be expected, its presence can be detected statistically from the data at hand. The degree to which it is a problem is essentially an empirical question and the first stages in the analysis is to detect whether it is indeed a problem.

4. Data and attribution

4.1. *Data*

4.1. The data made available to this study can be categorised under the headings; costs, demography, practice characteristics, income, morbidity, deprivation and socio-economics. These are described in turn in this section.

4.1.1 *Costs*

4.2. Our raw measure of utilization is prescription cost per head measured at the level of the GP practice. Cost is measured in pence and represents the net ingredient cost (NIC) of a prescription. This measure is independent of the peripheral costs of items such as containers and packaging, which may vary from prescription to prescription, and reflects the underlying cost of the treatment being prescribed.

4.1.2. *Demography*

4.3. Practice population demographics are measured in ASTRO-PUs. These reflect both the size of the practice list and its age, sex and temporary resident structure. Once costs are standardised by ASTRO-PUs they become more comparable across practices. Two versions of ASTRO-PUs are available; the original formulation of ASTRO-PU weights (Roberts and Harris, 1993) and revised weights (ASTRO(97)-PUs, Lloyd et. al., 1997). For the analysis set out here, we used the most up-to-date weights proposed by Lloyd et. al. (1997). ASTRO-PUs are used to standardise the cost data prior to modelling, hence utilisation data modelled was NIC per ASTRO(97)-PU. Appendix II presents details of the weightings for age, sex and temporary residents used to construct ASTRO(97)-PUs.

4.1.3. *Practice characteristics*

4.4. Practice characteristics available to the study where confined to fundholding status (and wave of fundholding); whether a practice had training status; whether a practice was dispensing (classified as a dispensing practice if more than a third of its patients were dispensing patients (GPs have authority to dispense directly to dispensing patients)); whether the practice was single-handed; the number of full time equivalent GPs and the practice list size.

4.5. In addition, five MEMPHIS variables were made available to us. The MEMPHIS report is supplied to all HAs and provides information on the prescribing costs incurred by practices for certain defined categories of drugs. It has been regarded as a useful indicator of practice prescribing cost-efficiency. The indicators provided for this study represent the percentage of all drugs prescribed generically, the costs of drugs of limited clinical value, the costs per prescribing unit of a list of combination products, the costs per prescribing unit of a list of modified release products and the number of daily defined doses of benzodiazepines per central nervous system STAR-PU (specific therapeutic equivalents to ASTRO-PUs (Lloyd, Harris and Roberts (1995)).

4.1.4. *Income*

4.6. The importance of income data in modelling utilisation using area analyses has been shown elsewhere (Carr-Hill et. al., 1997). More than 80% of items dispensed from prescription issued by GPs in England under the NHS are exempt from the prescription charge. Most exemption is based on age, but a large proportion is due to low income (approximately 12%), whilst another important category is Health Authority exemption which is mainly related to pregnancy. The low income scheme covers recipients of family credit and their dependants; recipients of income support and their dependants, and others who qualify on the grounds of low income. The importance of the low income scheme index (LISI) as a measure of deprivation for prescribing in general practice has been described by Lloyd, Harris and Clucas (1995). Related to these groups are patients who pay for prescriptions by purchasing a pre-payment certificate. Limited information of this nature can be obtained through prescribing exemption data obtained by the Prescribing Pricing Authority (PPA). Both exemption and pre-payment data are obtained from a 1 in 20 sample taken by the PPA. It is not produced for practices with a small list size (less than 1000) or where more than a third of the patients are dispensing patients, since they usually do not make a declaration.

4.7. Due to the lack of coverage of practices for which exemption data was made available, it was used for exploratory purposes only. Should such data become available routinely for all practices in the future, it may provide a valuable source of information for studies determining the utilisation of prescriptions.

4.1.5. *Mortality and morbidity*

4.8. Morbidity data available to the study consisted of standarised mortality ratios and standardised illness ratios, the latter defined from the self-report questionnaire in the 1991 Census of populations which asks individuals to assess whether they considered themselves as having a long term illness and whether, in their view, it limited their activities.

4.9. The standardised mortality ratio (SMR) was for ages 0-74 (SMR0-74). Its use is consistent with the development of the HCHS formula. The all-age SMR tends to be dominated by deaths in the elderly and it is difficult to dissentangle the effects of increased morbidity has over and above the inevitable consequences of ageing when using this variant. Further, the relationship between the ageing process and use of health care services, including the increased demand for prescriptions, will be captured, in part, by the use of ASTRO(97)-PUs. Consequently, we have opted for the 0 to 74 SMR which disregards the elderly.

4.10. Three variants of the Census limiting long standing illness question were considered in the analysis; the proportion of the total population of an area that self-reported limiting long terms illness; the proportion of children of an area that report limiting long term illness and the standardised illness ratio (ages 0 to 74).

4.1.6. *Deprivation*

4.11. The composite measure of area deprivation in common use that was considered in the analysis was the Jarman score (Jarman, 1983). The score itself is based on a sample of general practitioners' perceptions of factors affecting increased workload and is not a direct measure of deprivation. However, its use has received considerable attention in work of this nature. Because the component variables used to construct the score are derived from Census tables, we consider separately both the Jarman score itself and the component variables used in its construction.

4.1.7. *Socio-economics*

4.12. A multitude of Census socio-economic characteristics were available to the study. To focus on those factors thought, a priori, to be most indicative of prescribing utilisation, a selection of variables where chosen on the basis of advice of experts in this field and of similar work on needs based formula for NHS services. In particular, the set of socio-economic needs drivers found to be predictive of HCHS utilisation were included. A further twelve other variables were selected as potential correlates of prescribing utilisation.

4.13. Table definitions of all variables derived from Census data are provided as Appendix III. Appendix IV presents summary statistics together with correlations with cost data for all potential explanatory variables.

4.2. *Attributing indicator values to general practices*

4.14. The data made available for this study were derived from routine data sources and were required to be measured at the practice level. Commonly used sources of population need characteristics and socio-economic drivers of need when considering resource allocation formula are Census data. These were available at area level at either the electoral ward (or synthetic wards) or enumeration district. However, for the study described here, these data required attributing to individual practices.

4.15. The synthetic wards in question were formed by combining wards with populations of less than 5000. This reduces the number of wards in England and Wales at the time of the 1991 census from 9527 to 5304. It had the advantage of ensuring that numerators and denominators were non-zero for all but the most obscure of indicator components.

4.16. Two methods of attributing indicator values to general practices have been used to support the modelling of prescribing cost versus needs.

- Giving a practice the values of the indicators for the ward (or synthetic ward) where the main surgery is based. This approach was used in some preliminary analyses and then replaced by the following:

- Computing values based on the actual place of residence of the practice population.

4.17. The data on the place of residence of the practice populations were derived from a download of all patient registrations in England and Wales. By aggregating the raw registration data it is possible to compute the proportion of each practice population in each of the English EDs and wards.

4.18. The indicators can be attached to these practice population distributions at three levels: enumeration district, ward and synthetic ward. The procedure was the same for all three levels. The values of the indicator components (variables such as the proportion of persons in lone parent households) were computed for each of the relevant census units. These were combined with the proportions of a practice population in each census unit to give a weighted average for the practice. The indicator was then computed for the practice by combining its components according to the standard formula for the indicator.

4.19. Most of the indicators were attributed to the practice population at synthetic ward level. This was chosen for several largely pragmatic reasons to do with the availability and reliability of the data: for example, age specific standard mortality ratios were not available to the project for areas smaller than synthetic wards.

5. Modelling general practice prescribing expenditure

5.1. Section 3.2. sets out the theoretical model of the demand for health care on which this study was based. This section describes how the model was operationalised and estimated.

5.1. *Endogeneity of supply*

5.2. Equations (1) to (3) describe the system of equations that are necessary for the estimation of the demand for prescribing expenditure. The statistical problem that arises is that for each perceived supply variable *S*, there may be operating a simultaneous relationship of the sort:

$$U = f(N, S)$$

whilst (4)

$$S = f(U, N, X)$$

5.3. In other words, supply itself is a function of health care needs, other socio-economic factors and utilization. This problem is termed endogeneity and the variables *U* and *S* are termed endogenous variables, in the sense that they are determined within the system of equations. In contrast, the needs and socio-economic variables N and X are exogenous, in the sense that they are determined outside the system.

5.4. Endogeneity of this sort renders general statistical regression modelling such as ordinary least squares inappropriate leading to biased estimates of the supply coefficients of interest. In turn, this will bias the estimated needs coefficients since, in general, these will be correlated with supply. The problem stems from the fact that the residuals in equations (4) will be correlated. This means that estimation of (1) alone using OLS will invalidate assumptions of independence of residuals since the endogenous supply variables will be correlated with the error disturbance. Econometricians have developed analytical techniques to test for endogeneity, and to correct for it when it is found. Essentially, the methods break the correlation between the endogenous supply variables and the residuals in the utilization equation (1).

5.5. The methods adopted to correct for the endogeneity of supply rely on having a set of variables which are used in a separate regression to predict the endogenous supply variable. These variables are termed instruments and are often defined separately to the set of needs and wider socio-economic variables.

5.6. The supply variables used in this study were, on the whole, dichotomous variables denoting the presence or absence of practice status such as fundholding, training, dispensing, and whether single-handed. Of these, fundholding status was thought most likely to be defined endogenously with utilisation. The econometric methods for correcting for endogeneity for a dichotomous supply variable is achieved through regressing fundholding status on the instrument set and from the resulting residuals computing what is termed the Mill's ratio. This is then inserted alongside the set of needs and supply variables in the utilisation model of interest to be regressed on costs. Technical details of this procedure are provided in Appendix I.

5.2. *Additive and multiplicative model specifications*

5.7. In order to estimate equation (1) above the exact functional form of the relationship between health care needs, supply and utilization is required. This may take the form of an additive or multiplicative relationship. In its additive form, the statistical representation is as follows:

$$U = \alpha + \sum_{j=1}^{m} \beta_j N_j + \sum_{k=1}^{n} \gamma_k S_k + e \qquad (5)$$

5.8. Model (5) links the set of m needs variables and n supply variables to utilization in a linear fashion through the respective estimated coefficients represented by β_j, and γ_k. α represents a constant term and e is the usual error term. Utilization, *U,* in model (5) represents *NIC* per *ASTRO(97)-PU*.

5.9. The results of estimating model (5) may be interpreted in the following manner. The estimated coefficients attached to the needs variables represent the additional amount of spend in terms of *NIC* per *ASTRO(97)-PU* resulting from a one unit increase in the needs variable. The coefficient α, whose magnitude is also estimated from the data, represents the average *NIC* per *ASTRO(97)-PU* across the total population of practices and hence measures the average age, gender and temporary resident adjusted spend on prescriptions per capita in a year.

5.10. The alternative functional form is a multiplicative model of utilization which is specified as follows:

$$U = \alpha \prod_{j=1}^{m} N_j^{\beta_j} \prod_{k=1}^{n} S_k^{\gamma_k} \tag{6}$$

5.11. The estimated coefficients, $\hat{\beta}_j$ of model (6) indicate the elasticity of utilization with respect to the needs variables N_j. They can be interpreted as the percentage increase in utilization brought about by a 1% increase in need N_j.

5.12. In the absence of any particular over-riding theoretical justification for the elimination of one of the two specifications, the choice of which to use is largely an empirical question. In the work presented here, both linear and multiplicative models were tested.

5.13. Both models contain a set of supply variables to control for the influence practice supply characteristics may have on the estimated coefficients of need (thereby adjusting for correlations between supply and need) and to obtain good model specification (robust model fit).

5.14. Full details of both the additive and multiplicative model specifications are described as Appendix V.

5.3. ***Modelling hierarchical data***

5.15. A fundamental assumption of conventional statistical regression modelling is that the residuals (unexplained differences between observed values and estimates obtained from the model) are independently distributed. However, as Carr-Hill et al. (1994) point out, it is quite possible that systematic effects of health care administrative areas on utilisation rates exist. Examples cited in Carr-Hill et. al. include: a DHA policy to carry out some minor procedures in outpatient clinics leading to a depression of inpatient rates in all wards within the HA; or DHA practice in defining completed consultant episodes may have a systematic impact on utilisation rates throughout the District. Accordingly, in practice, it is plausible to suggest that there may be clustering of residuals within administrative areas.

5.16. Failure to account appropriately for the clustering of observations within higher level units (termed 'intra-class' correlation) may have severe implications for the inferences drawn from an analysis. Single level linear regression methods such as OLS are based on the assumption of independently distributed residuals. Where this assumption is violated, estimates of standard errors are downwardly biased. This means that confidence intervals tend to be too narrow and hence standard hypothesis testing may lead to erroneous results with coefficients appearing significant at standard levels when, in fact, they are not.

5.17. A potentially more serious concern is where failure to account explicitly for the intra-class correlation leads to a different needs gradient than would otherwise be observed if correct statistical and econometric techniques had been employed. Figure 2 depicts a series of observations on individuals in postcode sectors (for example, the rate of unemployment derived from Census statistics) within five Health Authorities. A standard regression model (ordinary least squares (OLS)) would consider each ward observation independently of the authority from which it came. In such situations a regression of utilisation against rate of unemployment (for example) may result in the regression line labelled 'OLS'. However, if we consider the same regression but this time within each authority we see a different relationship forming. The regression line within each authority is of a similar slope but each has a distinctly different intercept. A pooling (weighted average) of these within authority regression lines produces an 'overall regression' depicted by the line labelled 'True gradient'. It is this line that we wish to estimate. Clearly, the relationships depicted in Figure 2 are extreme and are unlikely to occur in practice; however, the general principles still apply to less transparent examples and situations.

5.18. Various regression procedures exist to model the relationship depicted in Figure 2. These can be conveniently classified under fixed and random effect models which have been discussed extensively in the econometrics literature, particularly when considering panel data analyses (for example, see Hsiao, 1995). Multilevel models have been developed by statistical educationalists and are a specific case of random effect models. There application to health data are described elsewhere (Rice and Leyland (1996), Rice and Jones (1997)). In their simplest forms, multilevel models may be considered as the same as variance component random effects models. Where more elaborate models are considered (for example, the inclusion of random coefficients to describe variability observed at a particular level, or the modelling of more than two levels) multilevel models have distinct advantages over other random effects models.

5.19. The relative strengths and weaknesses of fixed and random effects specifications in the context of resource allocation methodology have been set-out in a technical note to the Department of Health (Rice, 1998) and are not described in detail here. Hausman (1978) proposed a test statistic designed specifically to address the issue of correct specification and the modelling procedures adopted in this study were guided by these principles.

5.20. The choice of specification requires careful consideration and may be determined by the data generating process and/or, the type of inference sought. If Health Authorities (and their estimated effects) are not of intrinsic importance in themselves, but moreover are assumed to be random draws from a population of such individuals and that inferences concerning population effects and their characteristics are sought then a random specification may be more suitable. However, if inferences are to be confined to the effects in the sample only, and that these effects are of substantive interest then the effects themselves are more appropriately considered fixed (see for example, Hsiao 1995, p41).

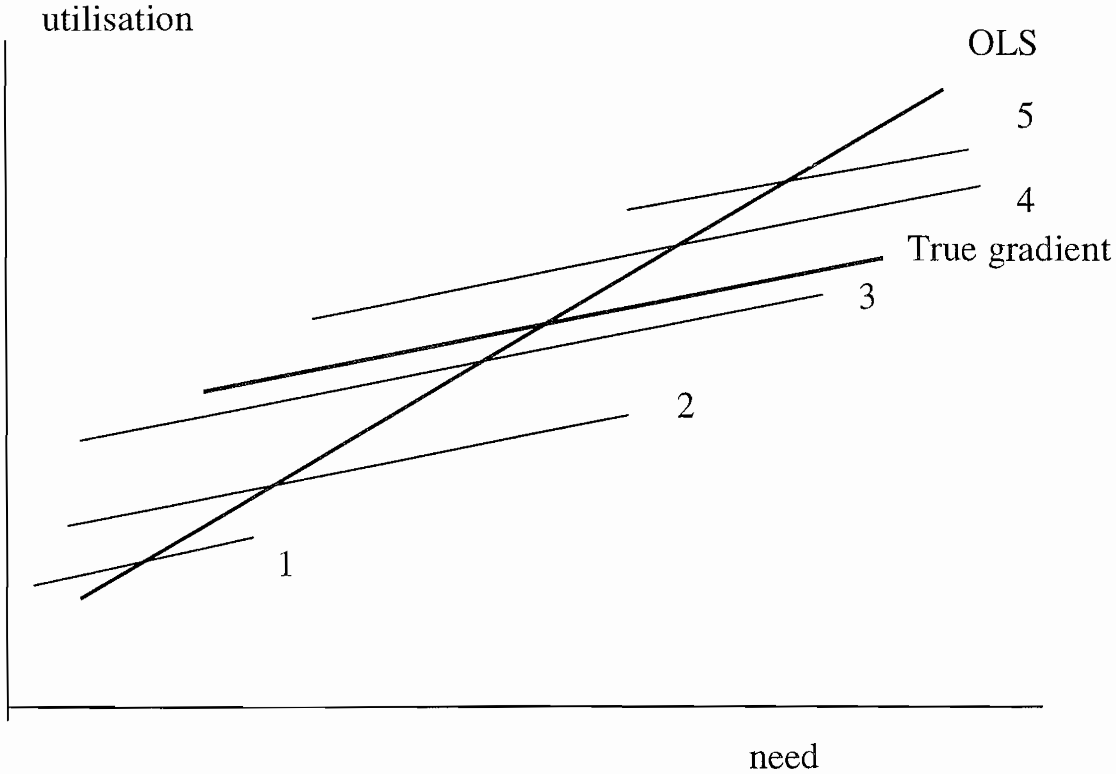

Figure 2. Hierarchical models against traditional (OLS) regression

5.21. An important consideration in choosing between the two specifications is when a needs variable is correlated with the health authorities effects. In such circumstances, a random or fixed effects approach may lead to vastly different estimates, and again careful consideration of the model specification is warranted (see for example, Hsiao 1995, p41, and Hausman 1978).

5.22. By fitting a series of dummy variables to represent Health Authorities effects in the fixed effects model, the specification purges coefficient estimates of correlations in much the same way as variables considered to be collinear are purged of correlation when fitted together in a single level equation. In the random effects specification, Health Authorities are treated in much the same way as residuals and do not enter the right-hand-side of a regression equation as explanatory variables. Hence coefficient estimates of needs variables are not adjusted for the correlations that may exist between needs and Health Authority effects. However, note that when group sizes are large, the two estimators can be shown to be equivalent (see Blundell and Windmeijer, 1997).

5.23. In the situation where an explanatory variable is correlated with the higher level effects, consistent estimation is achieved through a fixed effects specification. However, this is at the cost of inefficient estimation since we include a set of *j-1* dummy variables in the regression equation. In certain circumstances this may be expensive. Conversely applying a random effects specification in such situations will lead to efficient estimates, but these will be biased and inconsistent as the number of higher level groups approaches infinity. For intermediate situations where the trade off between consistency and inefficiency is unclear, application of the Hausman test (Hausman, 1978) may shed light on the most appropriate specification if substantive considerations do not already dictate this decision.

5.4. *Checks for endogeneity and misspecification*

5.24. Statistical tests exist to check for endogeneity of supply. These were performed for all models as described in full in Appendix I. Where endogeneity is found to exist two procedures are commonly used to overcome the statistical problems this creates. For continuous supply variables, the method of two-stage least squares is used and where supply variables are dichotomous (e.g. fundholding or not) evidence of endogeneity is controlled for by inserting what is termed the Mill's ratio as an additional regressor in the regression equation. These are very technical solutions to the statistical problem of endogeneity but have been used elsewhere in developing resource allocation formulae of the type presented here.

5.25. Once a final model of utilization was obtained, it was necessary to test that the model was well specified. This is a check to ensure that the model adhered to all requirements of econometric and statistical criteria applicable when using methods such as ordinary least squares. Ramsey proposed as a general test of misspecification the RESET test (Ramsey (1965)). This consists of obtaining the predicted values for the chosen model under test, calculating the second, third and forth powers of these values and then re-estimaing the regression equation with these three additional terms as extra regressors in the model. Should the terms prove statistically significant, there is evidence of model misspecification.

5.5. *Selection of needs variables*

5.26. We are interested in finding as parsimonious a model as possible: that is, a model with the least number of variables which sensibly capture variations in supply-adjusted utilization. However, for transparency, this model needs to be intuitively plausible. That is, any final model put forward as a serious contender upon which allocations are to be based should contain needs variables with coefficients exhibiting the sorts of relationships with expenditure we would expect to find. For example, we should expect that increases in the proportion of people reporting limiting long term illness will be related to increased utilisation and increased prescribing expenditure. An observed negative estimated coefficient on this variable would indicate that it may be working in tandem with some other variable with which it is highly correlated (for example, standardised mortality ratio). Much of Census derived needs variables are highly correlated and it is not uncommon to observe two variables operating in tandem with one offsetting the effects of another. Often when one of these is removed, the other variable also becomes non-significant. To ensure that as parsimonious and transparent a model as possible is found a sensible selection procedure needs to be adopted. As well as being good statistical practice, this results in a formula which is not too large or complex. The methodology adopted represents a "general to specific" scheme of model selection. In the first instance this included the fitting of the full set of potential needs variables. Needs variables were then removed from the model based on the following criteria in order of sequence:

- remove if counter-intuitive sign and coefficient is significant
- remove if counter-intuitive sign and coefficient is not-significant
- remove if not-significant

5.27. The procedure outlined not only ensures that a parsimonious model is found, but that variables acting jointly to offset the effects of one another are removed from the model. Only one variable was removed at a time, and hence allowing all variables an equal opportunity in the selection procedure.

5.28. Throughout, each observation, representative of a practice, was weighted by its list size. This ensures that, in seeking to infer a national average model of utilization, undue weight (after controlling for differences in supply) is not given to patterns of utilization in smaller practices.

5.6. *Role of supply in utilization models*

5.29. In developing a resource allocation formula, we wish to correct for variations in supply between practices. Effectively, this means assuming that all supply in a practice is at some national average level appropriate to the level of need found in the practice. In calculating a measure of relative need, therefore, the variation in utilization due to variation in supply variables should be considered only to the extent that supply reflects variations in legitimate need for health care. The requirement is to develop a measure of "normative utilization": the utilization that would be obtained in a practice if the response to its need was at the national average level. By including the supply variables in the regression equation whilst estimating the effects of needs variables, we are effectively controlling for such differences in practice supply and estimating needs assuming a national average supply profile.

6. Results

6.1. This section presents the results from the regression analysis of practice needs and supply on costs. Each of the tables of results presents variables under their appropriate heading of needs or supply. An additional variable, *gpfhmill*, is included to correct for any potential endogeneity of GP fundholding status as discussed in section 5.1. A full list of variables available to the study including summary statistics together with correlations with costs per capita and costs per ASTRO(97)-PU are given in Appendix IV.

6.1. *Demography, supply and needs*

6.2. Previous work has shown that model fit and stability is greater when the dependent variable is constructed as cost per ASTRO(97)-PU rather than modelling cost alone and fitting ASTRO(97)-PUs as a right hand side variable. This form of regression model was adopted throughout. Variables exhibiting a positive coefficient are indicative of increased practice prescribing cost with increased values of that variable. Negative coefficients are indicative of lower prescribing costs.

Variables were considered to be statistically significant if *t-values* were greater than 2 and non-significant otherwise.

6.3. To illustrate the explanatory power of ASTRO(97)-PUs, the first two sets of columns of Table 1 present ordinary least squares regressions of cost per patient on supply variables and cost per patient on supply and ASTRO(97)-PUs. The R^2 values represent the amount of variation explained within authorities, between authorities and in total. As can be seen the supply variables alone explain a negligible amount of variation in total cost (approximately 6% overall, but nearly 8% across Health Authorities), whilst the inclusion of ASTRO(97)-PUs explains an additional 30%.

6.4. The coefficients attached to the supply variables exhibited the expected signs. In general, dispensing practices were more expensive, as are non-training practices. Single handed practices tended to be cheaper (the hypothesis being that such practices find it difficult to respond to the demands of patients and hence take longer to see patients on their lists) and the more GPs per patient, the more expensive the practices were in terms of prescribing spend (the more GPs, the more quickly they can see patients, leading to a higher turnover rate). As expected fundholding practices were, in general, cheaper than non-fundholders.

6.5. It is important to note that the supply measures were included only to ensure a correct calibration of the needs coefficients. As such they played an important role in achieving the correct specification of the model so that the estimated 'needs' coefficients were adjusted for supply, but have no role in setting allocation targets. Only the set of estimated needs coefficients should be used for this purpose. There is no intention to use GP supply characteristics in a subsequent resource allocation formula.

Model description:	Supply effects		Supply & demography effects		Supply, demography and permanent sickness	
Dependent:	Dep - NIC/patient (costpp)		Dep - NIC/patient (costpp)		Dep - NIC/ASTRO(97)-PU (costas97)	
Variables	Coef	t-val	Coef	t-val	Coef	t-val
cons	77.948	45.11	-5.541	-2.905	17.092	50.68
ASTRO(97)-PU			18.291	64.97		
Need						
ppsick					0.775	16.92
Supply						
disprac	5.205	8.26	1.135	2.19	0.671	5.32
nottrain	3.529	7.95	2.309	6.36	0.507	5.87
gpsppat	10352.75	9.89	2714.72	3.15	672.39	3.30
singlep	-2.023	-4.07	-1.650	-4.07	-0.449	-4.64
gpfh	-4.284	-9.55	-4.27	-11.66	-0.983	-11.27
gpfhmill	-1.562	-1.19	8.390	7.73	-0.790	-2.49
R^2 - within	0.043		0.363		0.065	
R^2 - between	0.076		0.339		0.545	
R^2 - overall	0.055		0.356		0.178	

Table 1. Modelling supply, demography and needs effects.

6.2. Health Authority allocations

6.6. The 'benchmark' to which any practice level prescribing model may be compared is a model based on permanent sickness alone (using cost per ASTRO(97)-PU as a dependent variable). This is the current basis for setting allocations to Health Authorities and in the absence of anything more sophisticated is likely to be the default for setting practice level budgets.

6.7. The third set of columns of Table 1 present a summary of a model regressing cost per ASTRO(97)-PU against permanent sickness (*ppsick*), after controlling for supply characteristics. The estimated coefficient was positive, as expected, indicating that greater levels of area permanent sickness lead (on average) to greater costs of prescribing. Overall, the R^2 value increased to 18% (note that the majority of the variance explained is across authorities). This 18% represented the unexplained variation in cost per ASTRO(97)-PU and hence was additional to the 30% already explained by the inclusion of the age-sex weighting.

6.3. *Model for predicting prescribing expenditures*

6.8. Entering all potential determinants of prescribing utilisation in an inital regression together with the set of supply variables, and eliminating variables one at a time on the basis of the criteria set out in section 5.5. above, the model presented in Table 2 below was identified. Health Authority effects were modelled by including a set of dummy variables; this corresponds to a fixed effects model described in section 5.3. Further an additive model was chosen on the basis of superior model fit (see section 6.4. below).

6.9. The model in Table 2 contained an additional variable, *listinfl*, representing an estimate of practice list inflation. This was calculated by attributing Health Authority list inflation for five-year age and gender groups to practice populations within their respective HAs. It was included to correct the estimated coefficients on the needs variables from any correlation that may exist between need and list inflation. This was to ensure that the estimated needs gradient was not distorted by differences in practice list inflation.

6.10. The needs variables captured in the model presented in Table 2 are intuitively sensible. Permanent sickness (*ppsick*) and standardised illness ratio (*stdilln*) are capturing health characteristics, the percentage of babies in the population *(perc. babies*) is likely to be captured a dual effect of women of child bearing years (increased costs associated with pregnancy and contraception) and the increased demands brought about by treating babies. In part, these latter demands will have been reflected in the ASTRO-PU weights, but not perfectly. The proportion of dependants in no carer households (*pnocare1*) may, in part, also be reflective of an age effect (elderly), but also captured home circumstances and dependence on social and medical support.

6.11. The proportion of students (*pstudent*) had an estimated negative sign attached to it, indicating decreased prescribing costs for areas which send a higher proportion of their population to higher education. This is likely to be reflecting various phenomena; firstly students tend not to reside at the same address both during and outside term times and so make less use than others of local services, and secondly, it is capturing home circumstances as, in general, students tend to be of middle-class origin.

Model description:		
Dependent:	Dep - NIC/ASTRO(97)-PU (costas97)	
Variables	Coef	t-val
cons	24.305	22.555
Need		
ppsick	0.332	5.194
stdilln	0.012	2.570
pnocare1	0.029	2.353
pstudent	-0.256	-10.121
perc. babies	1.865	17.040
List inflation	-0.081	-7.834
Supply		
disprac	0.685	6.733
nottrain	0.317	3.931
gpsppat	884.59	4.085
singlep	-0.506	-4.595
gpfh	-1.156	-17.425
gpfhmill	-0.309	-0.915
R^2	0.405	
RESET		
$F(3, 8397)$	0.89	p=0.446

Table 2: Prescribing model

6.12. Including the practice level estimates of list inflation (*listinfl*) had a marginal impact on the estimated needs coefficients indicating that the model is relatively stable. The resulting model exhibits a non significant RESET statistic, indicating good functional form and a lack of omitted variable bias or deviation from normality. The RESET statistic is a general test statistic designed to pick up various aspects of model misspecification (Ramsey, 1969). The reported R^2 is relatively large, but is somewhat inflated as it includes the effects of fitting Health Authority dummy variables. Diagnostic probability plots of the residuals from the model showed no serious deviations from normality.

6.4. *Additive versus multiplicative models*

6.13. Adopting the final model in Table 2 the differences between an additive and multiplicative specification are presented in Table 3. For the additive model, the RESET is clearly non-significant indicating good model specification. However, in the multiplicative model, the RESET test is highly significant indicating poor model fit. Adopting a multiplicative approach and allowing other 'needs' variables to enter the model freely failed to identify a model which passed the RESET test. Additive models consistently outperformed multiplicative models using these data and was the chosen functional form.

Model description:	Additive model		Multiplicative model	
Dependent:	Dep - NIC/ASTRO(97)-PU		Dep - Ln(NIC/ASTRO(97)-PU)	
Variables	Coef	t-val	Coef	t-val
cons	24.305	22.555	5134.44	19.461
Need				
ppsick	0.332	5.194	0.084	6.606
stdilln	0.012	2.570	-0.016	-0.694
pnocare1	0.029	2.353	0.017	1.704
pstudent	-0.256	-10.121	-0.087	-10.948
perc. babies	1.865	17.040	-11.137	-19.438
List inflation	-0.081	-7.834	-0.570	-9.825
Supply				
disprac	0.685	6.733	0.038	7.065
nottrain	0.317	3.931	0.020	4.750
gpsppat	884.59	4.085	0.014	2.302
singlep	-0.506	-4.595	-0.037	-6.220
gpfh	-1.156	-17.425	-0.056	-15.995
gpfhmill	-0.309	-0.915	0.015	0.707
R^2	0.405			0.403
RESET				
$F(3, 8397)$	0.89	p=0.446		
$F(3, 8391)$			20.67	p<0.000

Table 3. Comparison between additive and multiplicative specification.

6.5. *Fixed versus random effects*

6.14. Representing Health Authority effects as a set of dummy variable in the so-called fixed effects model contrasts to the approach adopted in other resource allocation formula where such effects have tended to be regarded as random and modelled by use of multilevel models. The choice of specification can, in many applications, be informed by a test statistic known as the Hausman test (Hausman 1978). Essentially, the test compares the resulting coefficients estimated by both a fixed and random effects specification. If the differences are considered to be statistically different then a fixed effects specification is advised. This is because any differences observed between the two methods will be due to correlations between the variables of interest and the effects due to Health Authorities. Whilst a fixed effects approach makes appropriate adjustments for such correlations, a random effects approach does not. It ought to be pointed out that for large sample sizes the effect of such correlations becomes trivial and random effects models have some advantages here. This was the case in the modelling of HCHS where a multilevel approach was adopted.

6.15. Table 4 presents the results of comparing a fixed and random effects approach to these data. The Hausman test rejects the null hypothesis of no difference between the estimated coefficients derived from the two models indicating that a fixed effects specification is appropriate.

Model description:	Fixed effects		Random effects	
Dependent:	Dep - NIC/ASTRO(97)-PU		Dep - NIC/ASTRO(97)-PU	
Variables	Coef	t-val	Coef	t-val
cons	24.305	22.555	28.007	25.169
Need				
ppsick	0.332	5.194	0.442	6.176
stdilln	0.012	2.570	0.010	1.920
pnocare1	0.029	2.353	0.037	2.620
pstudent	-0.256	-10.121	-0.179	-6.326
perc. babies	1.865	17.040	2.062	19.376
List inflation	-0.081	-7.834	-0.121	-11.173
Supply				
disprac	0.685	6.733	0.850	6.850
nottrain	0.317	3.931	0.464	5.600
gpsppat	884.59	4.085	649.94	3.323
singlep	-0.506	-4.595	-0.467	-5.031
gpfh	-1.156	-17.425	-1.012	-12.163
gpfhmill	-0.309	-0.915	-0.726	-2.063
R^2	0.405		0.278	
RESET				
$F(3, 8397)$	0.89	p=0.446		
χ^2_3			3.80	p=0.284
Hausman test[⊥] - χ^2_{12}			155.7	p<0.000

Table 4. Comparison between fixed and random effects specification.
[⊥]Ho: difference between fixed and random effects not systematic.

6.6. *Role of supply*

6.16. All models presented were derived on the assumption that the set of 'needs' variables of interest were associated with supply. This was the rationale behind choosing a modelling strategy that included the set of supply variables in the model when deriving the coefficients on 'needs'. We also assumed that endogeneity between supply and demand was a potential problem. These assumptions were tested explicitly by removing the variable *gpfhmill* (variable used to control for potential endogeneity) and the set of supply variables and observing what effect this had on the coefficients associated with the 'needs' variables.

6.17. Table 5 presents the results of removing the variable *gpfhmill* and the supply variables. Removing the variable *gpfhmill* had a small effect on the estimated coefficients of 'needs'. The coefficient of permanent sickness reduced slightly as did those for standardised illness ratio and proportion of dependents with no carers. The coefficient on students increased marginally. Removing the set of supply variables had a much greater effect on the estimated coefficients of 'needs'. The coefficient for permanent sickness increased and played a more dominant role in the equation. This was offset to some extent by decreases in the estimated coefficients for the other 'needs' variables.

6.18. The net effect of removing the supply variables from the modelling was to produce a model with a slightly less steep 'needs' gradient than the model with supply. This suggests that the supply measures were picking up some of the higher levels of prescribing associated with high GPs per capita and dispensing practices etc.

	Preferred model without gpfhmill		Preferred model without supply	
	Dep - NIC/ASTRO(97)-PU		Dep - NIC/ASTRO(97)-PU	
Variables:	Coef	t-val	Coef	
cons	24.156	22.678	25.061	23.451
Need				
ppsick	0.328	5.147	0.366	5.615
stdilln	0.010	2.415	0.008	1.867
pnocare1	0.032	2.621	0.022	1.826
pstudent	-0.266	-11.555	-0.254	-10.802
perc. babies	1.861	17.017	1.833	16.469
List inflation	-0.081	-7.814	-0.085	-8.021
Supply				
disprac	0.667	6.685		
nottrain	0.318	3.940		
gpsppat	869.43	4.027		
singlep	-0.509	-4.624		
gpfh	-1.151	-17.407		
gpfhmill				
R^2	0.405		0.376	
RESET				
$F(3, 8392)$	0.88	p=0.449		
$F(3, 8397)$			0.46	p=0.708

Table 5: Role of supply

6.7. *Recommended model*

6.19. The model presented in Table 2 represents our best efforts to derive a robust needs based formula for allocating prescribing monies. The variable representing the percentage of people unable to work due to permanent sickness was derived from Census data. Currently there are two versions of permanent sickness used in weighted capitation formula. The first, used in the psychiatric needs formula, is defined as the "percentage of residents aged 16 and over (no upper limit and not just residents in households) who are economically inactive due to permanent sickness." The second, in use as the needs adjustment for Health Authority prescribing allocations, has the following definition, "percentage of residents in households aged 16 and over (no upper limit) who are economically inactive due to permanent sickness". Because the first version was already used in the HCHS formula for psychiatric need it was readily available at synthetic ward level and could be assigned to practices using the attribution method described in section 4.2. This is the definition of permanent sickness used thus far in this report.

6.20. When presenting this work to the Technical Advisory Group (TAG) of the Advisory Committee on Resource Allocation (ACRA), they asked that the second definition of permanent sickness be used instead. It was felt that this definition better reflected relative morbidity than the first since it was not confounded with institutional populations in hospitals, prisons, hostels and nursing homes. As such, this alternative definition of permanent sickness was constructed at synthetic ward level and attributed to practices.

6.21. Substituting the versions of permanent sickness had the effect of adjusting the coefficients on the other needs variables. These alterations were minor except for limiting long term illness which became non-significant. Removing this latter variable and re-estimating resulted in a model with fewer needs variables (four as opposed to five), but with similar explanatory power (approximately 41%) as the previous model presented in Table 2. The estimated supply coefficients changed by less than 2%.

6.22. As a further check of the robustness of this model with the alternative definition of permanent sickness, the modelling process of selecting variables was re-run from scratch with this preferred definition. Adopting the same procedures as those used to derive the model in Table 2, the same four-variable model of permanent sickness (preferred definition), percentage of dependants with no carers, percentage of students and percentage of babies was obtained. The estimated coefficients and standard errors for this model are presented in Table 6. Diagnostic plots for this model are provided as Appendix VI; no serious departures from normality are observed.

	Recommended model	
	Dep - NIC/ASTRO(97)-PU	
Variables:	Coef	t-val
cons	24.99	23.106
Need		
ppsick2	0.594	11.399
pnocare1	0.027	2.172
pstudent	-0.233	-9.241
perc. babies	1.88	17.572
List inflation	-0.083	-8.094
Supply		
disprac	0.682	6.808
nottrain	0.324	4.017
gpsppat	909.61	4.0210
singlep	-0.504	-4.585
gpfh	-1.145	-17.284
gpfhmill	-0.564	-1.749
R^2	0.406	
RESET $F(3, 8392)$	0.24	p=0.86

Table 6: Recommended models

6.23. The revised model presented in Table 6 was recommended to ACRA who duly accepted it. It represents the preferred model for use for allocating monies to Health Authorities and Primary Care Groups. For allocation purposes, the constant term requires deflating by 8.72. This is because the regression models contained a term for list inflation which was indexed to 100 across all practices, but averaged 105.1 in these data. List inflation was used within the model to correct for the possibility of correlations between itself and the set of needs variables. However, it was not intended for use for setting allocation budgets. When it was removed this was reflected in a decrease in the constant term of approximately 0.083×105.1=8.72. Accordingly, when calculating the share of monies to a practice, the revised constant of 16.27 (24.99-8.72) ought to be used.

7. *Conclusions*

7.1. This report summarises methods and results of a study to derive a robust needs based allocation formula for setting general practice prescribing budgets at Health Authority and Primary Care Group level. Table 6 presents the recommended model. It has good model specification and is capable of explaining up to 41% of variation in prescribing expenditure at practice level. This is in addition to approximately 35% already explained through adjustments made for the age, sex and temporary resident status of practice populations. The model derived represents a vast improvement on the current formula used to allocate monies to Health Authorities, and we have recommended that it can be used as a basis for allocating monies to Health Authorities and Primary Care Groups.

7.2. The data set used for this project represents by far the most comprehensive assembled to date for analysing prescription expenditure. With the exception of data on income status of practice populations it is difficult to imagine what additional information could be utilised to enhance the modelling procedures used for analysing practice level data.

7.3. The supply variables exhibit the signs expected and the selected needs variable are intuitively plausible. Permanent sickness captures health characteristics whilst the proportion of dependants with no carers is reflective of wider social circumstances. The inclusion of the proportion of babies is likely to capture both an effect of women of child bearing years and the increased demands of young children. The proportion of students is likely to be reflective of a variety of factors including those associated with young mobile healthy populations, and a lack of permanent residence.

7.4. Future work in this area would benefit from the inclusion of income data. This may take a number of forms but the inclusion of data provided through the low income scheme and income support data is likely to prove most valuable. The former is available, at present, for non-dispensing practices only, but has proved valuable for predicting prescribing expenditure on subsets of data and has the advantage of being defined at the practice level. Income support data will become more readily accessible in the future but will require attributing to practice lists.

7.5. The possibility for further refinements to the model presented here appear limited using current data sources. Gains in understanding the needs based mechanisms of prescribing may best be achieved through moving to data measured at the individual patient level. Although, for the foreseeable future it appears unlikely that such data will be collected on a routine basis, much could be gained from a survey of individual patients and their practices. This may form the basis of a future research agenda not only in the area of prescribing, but also to inform resource allocation methodology in other areas of the NHS budget.

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Appendix I: *Endogeneity of utilisation and supply*

The general form of the equation of interest is as follows:

$$U_i = X_1\beta_X + N_i\beta_N + S_i\beta_S + e_i \qquad \text{(AI.1)}$$

where $S_i = GPFH_i + DISP_i + A_i + GP_i$ (AI.2)

In model (AI.1), measures of need are contained within the set of variables labelled *N*, whilst wider socio-economic variables are captured within *X*. Practice supply characteristics are modelled by *S*, which consists of the following variables: *GPFH* representing the fundholding status of a practice (1 if fundholder or group fundholder; 0 otherwise); *DISP,* the dispensing status of a practice (1 if practice list contains dispensing patients; 0 otherwise); *A* a measure of accessibility of GP services and *GP* capturing other supply characteristics of practices.

Need and socio-economic variables are assumed exogenous to the system and may be incorporated in the usual manner in a regression framework. In contrast, the supply variables require a different approach. We assume, a priori, that the supply of health care is not exogenous but is determined endogenously with the demand for health care (expressed here in terms of utilisation). If such a representation is justified in these data, standard regression methods will lead to biased and inconsistent parameter estimates for the coefficients β_S. This, in itself, is not of great importance, since for resource allocation purposes we are concerned with the exogenous estimates $\hat{\beta}_N$ and $\hat{\beta}_X$. However, should any of the set of needs and socio-economic variables be correlated with supply (which is to be expected) then the estimates of $\hat{\beta}_N$ and $\hat{\beta}_X$ will also be estimated with bias.

Statistical methods available for correcting for endogeneity of the type outlined above include instrumental variable techniques (for example, see Heckman and Robb, 1985) and two stage least squares (a specific version of instrumental variables). Both methods rely on the analyst having sufficient instruments (set of exogenous variables) that satisfy the following criteria:

- they are highly correlated with the potentially endogenous supply variable
- they are uncorrelated with utilisation.

For these data, instruments are required that predict supply but are unrelated to utilisation. In practical situations, these conditions are often difficult to meet and in these data there is little, a priori, justification in supposing that any of the variables meet such criteria.

Instrumental variables

If we can find suitable 'instruments' (we shall denote these Z_i) for the endogenous supply variables, we can construct instrumental variables which are purged of correlation with the error term e_i allowing us to estimate a consistent parameter values for supply, and hence need and socio-economic correlates of utilisation.

Instruments are additional exogenous variables which satisfy a number of (asymptotic) properties. First, they are uncorrelated with unobserved determinants of health status (e_i):

$$E(Z_i, e_i | X_i) = 0 \tag{AI.3}$$

Secondly, they are (strongly) correlated with the potentially-endogenous variable (for example, $GPFH_i$):

$$E(Z_i, GPFH_i | X_i) \neq 0 \tag{AI.4}$$

In this way, valid instruments are legitimately excluded from the structural outcome equation, but belong in the reduced form equations predicting *GPFH* status. In the example considered here, the instruments predict fundholding status, but are unrelated to the cost of dispensing directly (their influence on costs will only occur through *GPFH* status). The 'instrumenting variable' for *GPFH* status is estimated by the predicted value $GPF\hat{H}_i$ from the reduced form equation:

$$GPFH_i = X_i\beta_X + N_i\beta_N + Z_i\beta_Z + w_i \tag{AI.5}$$

Once predictions from this model are obtained they are used in the structural equation such that:

$$U_i = X_i\beta_X + N_i\beta_N + S_i\beta_S + e_i \tag{AI.6}$$

where $S_i = GPF\hat{H}_i\beta_{GPFH}$

As $GPF\hat{H}_i$ is uncorrelated with e_i by design, we can obtain selection-free (or endogenous free) estimates of $\hat{\beta}_{GPFH}$.

Since many potential instruments may be sought, a formal test for their validity can be assessed by the so-called *J-test*. When the number of instruments *(p)* in our reduced form model exceeds the number of parameters of our structural model *(k),* then any one of the set of *(p-k)* instruments would be sufficient to identify practice fundholding status. Our model is termed 'over-identified'. Under these circumstances, the validity of the chosen instruments may be tested formally by the *J-test*. This is implemented by regressing the residuals e_i from our structural equation against the instruments X_i and Z_i. If the instruments are valid and the functional form of the outcome model is correct, the corresponding R^2 statistic should approach zero. This may be tested formally by observing that:

$$J = nR^2 \approx \chi^2_{(p-k)} \tag{AI.7}$$

When the model is only just identified such that *p=k*, then *J=0*. Accordingly, the method is only valid in overidentified models (i.e. $p > k$). If *J* is not significant, we may conclude that the model is correctly specified and that our instruments are valid.

To test whether the variable *GPFH* is infact prone to endogeneity bias, we can implement the so-called *H-test*. This consists of using the residuals, w_i from the reduced form equation as additional regressors in the structural equation as follows:

$$U_i = X_i\beta_X + N_i\beta_N + S_i\beta_S + \hat{w}_i\beta_w + e_i \qquad \text{(AI.8)}$$

where $S_i = GPF\hat{H}_i\beta_{GPFH}$ (AI.9)

The *H-test* is simply provided by the test of significance of the estimated coefficient, $\hat{\beta}_w$. If H is significantly different from zero, the null hypothesis of no endogeneity bias is not consistent with the data and may be rejected. In such circumstances, estimates of supply and need should be obtained from either equation, (AI.6) or (AI.8).[2]

Control functions

For supply variables that are dichotomous (such as *GPFH* status), an alternative approach to standard instruments that does not rely as heavily on the above assumptions is often more fruitful. This approach is an adaptation of a procedure proposed by Heckman for eliminating selection bias in survey data and is often termed a control function estimator.

The two-stage version of the control function estimator is implemented by first estimating the probability of the endogenous supply characteristic of interest (for example, *GPFH* status) by using a probit specification:

$$GPFH_i = Z_i\gamma + v_i \qquad \text{(AI.10)}$$

From this model, the inverse of what is termed the Mill's ratio (*IMR*, symbolised by $\hat{\lambda}_i$[3]) can be computed and inserted as an additional explanatory variable in the second-stage regression of the utilisation equation:

$$U_i = X_I\beta_X + N_i\beta_N + GPFH_i\beta_{GPFH} + \hat{\lambda}_i\theta + e_i^* \qquad \text{(AI.11)}$$

The inclusion of the *IMR* breaks the correlation between $GPFH_i$ and e_i and allows us to obtain consistent estimates of the parameters β_S and thence β_X and β_N.

The estimated coefficient $\hat{\lambda}_i$ represents the covariance between v_i and e_i (σ_{ev}), and its associated t-ratio provides a test of whether the null hypothesis of *no endogeneity bias* is consistent with the data.[4]

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[2] Both equations (AI.6) and (AI.8) produce the same estimates.

[3] Defined as $\hat{\lambda}_i = \dfrac{\phi[Z_i\hat{\gamma}]}{\Phi[Z_i\hat{\gamma}]}$, where ϕ represents the normal densiy function and Φ the cumulative density function

[4] Using standard levels of significance, a p-value of less than 0.05 is indicative of endogeneity of

An advantage of using the inverse Mill's ratio is that it does not require additional instruments;[5] however, one potential shortcomings is that identification may be fragile, as it relies solely on $\hat{\lambda}_i$ being a nonlinear function of the X_i (Heckman and Robb, 1985; Mullahy and Manning, 1995). Identification may be secured if we are able to include additional variables which satisfy two criteria: first, they are relevant in predicting *GHFH* status; and second, they can be legitimately excluded from the utilisation equation.

utilisation and supply.

[5] *Z* can consist of any variables predicting GPFH status including variables contained within *N* and *X*.

Appendix II: *Construction of ASTRO(97)-PUs*

Design:- 123 English practices from period November 1995 to October 1996. Data provided by IMS (Intercontinental Medical Statistics) including age and sex together with cost data for each practice. Authors argue that I. Costs weights used in original calculations are estimates only; II. Use of an integer scale distorts practice based allocations as under-weights males 15 to 34, and females 55 to 64 and over-weights males 75+ and females 65-74. From cost and age-sex data alone authors calculate revised as follows weights:

ASTRO-PU 97 weights	0-4	5-14	15-24	25-34	35-44	45-54	55-64	65-74	75+	Temporary residents
Male	1	1.4	1.7	2.0	2.8	4.4	7.6	10.1	11.8	
Female	0.8	1.2	2.1	2.4	3.2	5.4	7.2	9.6	10.6	
all ages/ both sexes										0.5

Appendix III: *Table definitions of variables derived from Census*

Variable	Data source[1]	Table	Definition
Deprivation indices:			
Jarman deprivation score			weighted sum of transformed component variables
1. People aged 16 or more seeking work as % of all residents	Local base stats	9	(109 + 301)/(25 + 217)
2. People in hholds living at more than 1 person/room as a % of all pop	Local base stats	23	(54 + 55)/51
3. Pensioners living alone as a % of all residents	Local base stats	47 and 1	(15 + 29 + 43 + 57 + 71 + 85)/65
4. People in hhold of one person over 16 and one or more children under 16 as a % of all pop	Small area stats	40 and 1	(1 + 61)/65
5. People in hhold headed by a person born in New Commonwealth or Pakistan as % of all pop	Local base stats	7	55/1
6. Children under 5 as a % of all residents	Local base stats	2	12/1
7. People in hholds headed by person in socio-economic group II as a % of all residents	Local base stats	86	177/9
8. People age 1 year or more with usual address one year before Census different from present	Local base stats	15 and 2.	1/1
Other Census socio economics characteristics:			
9. Standardised mortality ratio - under 75	Local base stats	N/A	100*((all cause obs deaths < 65 + 65-74)/(all causes exp. deaths <65 + 65-74))
10. Standardised illness ratio - under 75	Local base stats	12 and 35	
11. Perc. of those of pensionable age living alone	Local base stats	47	(15 + 29 + 43 + 57 + 71 + 85)/169
12. Perc. of economically active unemployed	Local base stats	8	134/20
13. Perc. of dependents in single carer households	Local base stats	30	(30 + 70)/10
14. Perc. of persons in lone parent households	Small area stats	32	(22 + 23 + 34 + 35)/(10 11)
15. Perc. of households with no car	Small area stats	49	57/1
16. Perc. of people who are single, widowed or divorced	Small area stats	2	(3 + 6)/1
17. Perc. of households lacking central heating	Small area stats	49	50/1
18. Perc. of dependents in no carer households	Small area stats	30	20/10
19. Perc. where head of household born in New Commonwealth	Small area stats	49	69/64
20. Perc. of adult population permanently sick (first definition used)	Local base stats	8	210/1
21. Perc. of adult population permanently sick (second definition used)	Small area stata	34	67/1
22. Perc. of persons aged 18+ with some qualifications	Small area stats	84	4/1
23. Perc. of households with three or more children	Small area stats	36	65/61
24. Perc. of children age 0-17 with limiting long term illness	Local base stats	2, 12, 13	(12:4+12:7+12:10+13:11+13:12+13:15+13:16+13:19+13:20+13:23+13:24:13:27+13:28+13:31++13:32)/
25. Perc. of total pop with limiting long term illness	Local base stats	1, 12, 13	(12:1+13:3+13:4+13:7+13:8)/total pop
26. Perc of dependent children in non-earning households	Local base stats	36	(6+12+18+30+48)/66
27. Perc. in households in crowded accomodation (> 1per room)	Local base stats	49	(183+196)/170
28. Perc. of persons in permanent buildings owner occupied	Local base stats	20	(412+413)/411
29. Perc. of persons in private rented	Local base stats	20	(414+415)/411
30. Perc. in Black ethnic groups	Local base stats	6	(3+4+5)/1
31. Perc. in Indian, Pakistani and Bangladeshi groups	Local base stats	6	(6+7+8)/1
32. Households with children	Local base stats	31	(39 to 43 + 63 to 67)/(1+2)
33. Perc. of working age pop who are students	Local base stats	8	(191 - 472 - 473 - 474 - 737 - 738 - 739 - 740)/(1-282-283-284-547-548-549-550)

34. Perc. of residents with different address to one year ago	Local base stats	15	1/total population
35. Perc. of econ active in manual SEG	Local base stats	92	(81+82+89+90+97=98+105+106+113+114+121+121+122+145+146)/ (1+2)
36. Density	Local base stats	1, area	Ratio of persons to area 0164 Hectors
Needs indices			
Acute index	NHS Executive		0.2528*10. + 0.1619*9. + 0.0287*12. + 0.07649*11. + 0.04362*13.
Community psychiatric	NHS Executive		0.128*15. + 0.8*16. + 0.13*14. + 0.519*9.
District nursing	NHS Executive		0.263*15. + 0.142*23. + 0.424*9.
Health visiting	NHS Executive		0.088*17. + 0.172*23. + 0.069*14. + 0.169*18.
Community maternity	NHS Executive		0.265*13.
Chiropody	NHS Executive		0.108*15. + 0.139*19. - 0.115*21. + 0.725*9.
Other community health	NHS Executive		0.108*15. * 0.532*16.
Inpatient psychiatric and PLD	NHS Executive		0.2426*10. + 0.3609+11. + 0.1073*19. + 0.1846*14. + 0.1431*13. + 0.2616*20.

[1] The 1991 census variables used in the needs indices are based on two separate sources of information: local based statistics and small area statistics. The small area statistics is an abbreviated version of the local based statistics, but n many cases the table numbers and cell addresses are different in the two sources.

Appendix IV: *Summary statistics*

Name	Variable	Data Source	n	Mean	Std. Dev.	Range	Correlation with NIC per capita*	Correlation with NIC per astro97*
	Dependents							
costpp	NIC per capita	PACT	8506	83.34	20.39	9.36 - 219.28	1	0.800
igenpp	NIC (adjusted for generics) per capita	PACT	8506	82.08	20.08	9.25 - 217.85	0.998	0.804
igenhipp	NIC (adjusted for generics and high cost drugs) per capita	PACT	8506	78.12	19.59	8.63 - 211.42	0.993	0.804
	Demographics							
astropp	ASTRO-PUs per capita	PSU	8506	3.65	0.59	1.38 - 7.09	0.514	-0.002
ast97pp	ASTRO(97)-PUs per capita	PSU	8506	4.24	0.62	1.63 - 8.51	0.600	0.024
oupp	Prescribing units (PU's) per capita	PSU	8506	1.32	0.11	1.00 - 2.13	0.521	0.015
	Income							
isi	Low income scheme index (LISI)	PSU	7734	15.56	9.89	0.76 - 76.58	-0.094	0.252
young	Young	PSU	7734	7.67	4.18	0.47 - 56.07	-0.275	0.006
old	Elderly	PSU	7734	41.12	10.26	1.75 - 80.59	0.393	-0.031
hsaexem	FHSA Exemptions	PSU	7734	7.68	3.16	0.00 - 51.77	-0.122	-0.061
prepay	Pre-payments	PSU	7734	5.87	2.94	0.00 - 23.47	0.140	0.090
varserv	War service	PSU	7734	0.25	0.39	0.00 - 7.02	0.058	0.133
	Morbidity							
mrund75	Standardised mortality ratio - under 75	Census	8506	102.94	18.97	46.00 - 178.04	0.032	0.301
tdilln	Standardised illness ratio - under 75	Census	8506	103.79	27.52	47.38 - 227.05	0.154	0.395
hllti	Perc. of children age 0-17 with limiting long term illness	Census	8506	2.39	0.59	0.88 - 5.61	0.030	0.249
opllti	Perc. of total pop with limiting long term illness	Census	8506	12.99	2.73	4.73 - 24.97	0.395	0.383
psick	Perc. of adult population permanently sick	Census	8506	3.94	1.77	0.79 - 14.54	0.247	0.430
psick2	Perc. of adult population permanently sick	Census	8506	3.66	1.76	0.77 - 14.51	0.237	0.436
	Socio-economic characteristics							
	Other Census socio economics characteristics:							
lnpens1	Perc. of those of pensionable age living alone	Census	8506	33.98	4.46	19.60 - 56.02	-0.183	-0.015
unempl	Perc. of economically active unemployed	Census	8506	10.18	4.98	2.72 - 34.74	-0.042	0.213
scarer1	Perc. of dependents in single carer households	Census	8506	20.24	5.06	8.61 - 39.26	0.069	0.228
lonpar1	Perc. of persons in lone parent households	Census	8506	9.72	4.89	1.97 - 31.87	-0.122	0.098
nocar	Perc. of households with no car	Census	8506	34.04	13.34	5.45 - 76.76	-0.055	0.166
swidivr	Perc. of people who are single, widowed or divorced	Census	8506	54.39	5.82	31.63 - 74.49	-0.316	-0.054
nocenth	Perc. of households lacking central heating	Census	8506	19.55	10.48	1.06 - 68.98	0.096	0.201
nocare1	Perc. of dependents in no carer households	Census	8506	15.06	3.89	3.58 - 38.06	0.243	0.164
newcom1	Perc. where head of household born in New Commonwealth	Census	8506	7.09	10.02	0.10 - 62.73	-0.331	-0.142
somqual	Perc. of persons aged 18+ with some qualifications	Census	8506	13.26	6.62	1.33 - 47.33	-0.291	-0.397
hh3kids	Perc. of households with three or more children	Census	8506	5.53	1.83	1.09 - 18.95	-0.124	0.170
inoearn	Perc. of dependent children in non-earning households	Census	8506	18.00	9.91	2.78 - 56.90	-0.071	0.189
rowhh	Perc. in households in crowded accommodation (> 1per room)	Census	8506	5.35	4.21	0.58 - 38.03	-0.262	-0.009
wnocc	Perc. of persons in permanent buildings owner occupied	Census	8506	69.24	14.19	11.91 - 96.14	0.182	-0.025
ntocc	Perc. of persons in private rented	Census	8506	6.46	4.72	0.63 - 43.46	-0.281	-0.266
lcketh	Perc. in Black ethnic groups	Census	8506	2.49	4.72	0.01 - 35.20	-0.336	-0.185
beth	Perc. in Indian, Pakistani and Bangladeshi groups	Census	8506	4.10	7.63	0.00 - 57.08	-0.216	-0.033
ichild	Households with children	Census	8506	25.16	4.51	8.25 - 42.93	0.024	0.128
student	Perc. of working age pop who are students	Census	8506	5.12	1.74	2.16 - 21.03	-0.279	-0.277
gmanual	Perc. of econ active in manual SEG	Census	8506	42.34	9.33	13.10 - 66.87	0.285	0.396
i171	Density	Census	8506	29.62	26.77	0.00 - 186.37	-0.330	-0.158
igrants	Perc. of residents with different address to one year ago	Census	8506	9.94	2.86	4.32 - 34.05	-0.330	-0.268
ognhome	Perc. of people over retirement age in nursing homes	Census	8506	1.10	1.15	0.00 - 20.89	0.164	0.079
75nhome	Perc. of elderly >75 yrs.) in nursing homes	Census	8506	2.38	2.42	0.0 - 37.54	0.164	0.087
ercb	Estimated percebtage of babies		8506	1.3	0.4	0.0 - 6.7	-0.165	0.162
	Needs indices							
cutei	Acute index	Census	8506	5.46	0.66	3.64 - 7.64	0.032	0.276
ompsyc	Community psychiatric	Census	8506	4.37	1.20	1.43 - 9.44	-0.154	0.096
iursc	District nursing	Census	8506	3.51	0.69	1.82 - 5.90	-0.073	0.205
ealthvc	Health visiting	Census	8506	43.56	4.98	23.39 - 60.35	0.032	0.118
ommnatc	Community maternity	Census	8506	65.10	4.26	52.22 - 78.05	0.036	0.180
iiropc	Chiropody	Census	8506	20.77	6.49	8.21 - 46.24	-0.221	0.052
hchc	Other community health	Census	8506	63.92	6.13	42.33 - 82.54	-0.229	0.004
ptpsyc	Inpatient psychiatric and PLD	Census	8506	29.26	9.76	9.04 - 72.03	-0.157	0.069

Name	Variable		Data Source	n	Mean	Std. Dev.	Range	Correlation with NIC per capita*	Correlati with NI per astro97p
	Practice characteristics								
nogps	Number of GPs		PACT	8506	3.11	1.96	1.00 - 16.00	0.032	-0.060
list	List size		PACT	8506	5794.8	36.92.7	1004 - 33041	-0.044	-0.087
numpart	Number of Partners		PACT	8506	3.10	2.01	0.00 - 16.00	0.031	-0.058
gpsppat	Number of GPs per patient		PACT	8506	0.001	0.00	0.00 - 0.004	0.177	0.072
	Supply/ access								
numpr3	Number of practices within 3KMs of ward of practice[2]		NHS Exec	8068	18.59	20.02	0 - 114	-0.345	-0.191
numpr5	Number of practices within 5KMs of ward of practice		NHS Exec	8068	43.54	50.65	0 - 246	-0.352	-0.207
numpr15	Number of practices within 15KMs of ward of practice		NHS Exec	8068	264.83	324.95	0 - 1232	-0.354	-0.230
	Performance indicators								
pergener	Percentage generic prescribing		PACT	8506	57.16	12.21	9.38 - 90.19	-0.055	-0.070
lcvpu	Cost of drugs of limited clinical value		PACT	8506	0.87	0.54	0.02 - 6.52	0.387	0.531
modrelpu	Cost of modified release preparation		PACT	8506	1.80	0.83	0.00 - 7.94	0.565	0.574
combipu	Cost of combined products per prescribing unit		PACT	8506	0.58	0.42	0.00 - 4.29	0.464	0.489
benzostr	Number of DDDs of benzodiazepines per CNS STAR-PU		PACT	8506	1.19	0.83	0.00 - 17.44	0.387	0.438
	Practice type								
	Cost/patient								
fholder	Fundholding practice -	- No	PACT	6949	83.67	21.51	t - value = 4.12	p-value= 0.000	
		- Yes		1557	81.84	14.27			
gfholder	Group fundholding practice	- No	PACT	7495	83.55	20.65	t - value = 2.78	p-value= 0.005	
		- Yes		1011	81.81	18.33			
gpfh	Group or individual fundholding practice	-Yes	PACT	2568	81.83	15.99	t - value = -5.08	p-value=0.000	
		- No		5938	83.99	21.99			
disprac	Dispensing practice	- No	PACT	7406	82.23	20.57	t -value = -14.93	p-value = 0.000	
		-Yes		1100	90.84	17.41			
nottrain	Not a training practice	- Yes	PACT	5973	84.43	19.69	t - value = -7.30	p-value =0.000	
		- No		2533	80.77	21.74			
singlep	Single handed practice	- No	PACT	6469	84.69	18.90	t - value = 9.66	p-value =0.000	
		- Yes		2037	79.06	24.04			
	Cost/astro97								
fholder	Fundholding practice -	- No	PACT	6949	19.82	4.22	t - value = 10.55	p - value = 0.000	
		- Yes		1557	18.92	2.73			
gfholder	Group fundholding practice	- No	PACT	7495	19.69	4.07	t - value = 2.91	p - value = 0.004	
		- Yes		1011	19.35	3.52			
gpfh	Group or individual fundholding practice	- Yes	PACT	2568	19.08	3.07	t - value = -9.86	p - value = 0.000	
		- No		5938	19.90	4.33			
disprac	Dispensing practice	- No	PACT	7406	19.62	4.12	t - value = -2.48	p - value = 0.013	
		-Yes		1100	19.88	3.12			
nottrain	Not a training practice	- Yes	PACT	5973	19.77	3.82	t - value = -4.00	p - value = 0.00	
		- No		2533	19.37	4.40			
singlep	Single handed practice	- No	PACT	6469	19.76	3.67	t - value = 3.90	p - value = 0.00	
		- Yes		2037	19.30	4.90			

* capita is defined by list size

[2] within X Kms of centroid of ward corresponding to practice postcode (presumed to be the postcode of the main surgery)

Appendix V: *Additive and multiplicative model specification*

Additive model specification

In order to estimate equation (1) above the exact functional form of the relationship between health care needs, supply and utilization is required. This may take the form of an additive or multiplicative relationship. In its additive form, the statistical representation is as follows:

$$U = \alpha + \sum_{j=1}^{m} \beta_j N_j + \sum_{k=1}^{n} \gamma_k S_k + e \qquad \text{(AV.1)}$$

Model (AV.1) links the set of *m* needs variables and *n* supply variables to utilization in a linear fashion through the respective estimated coefficients represented by β_j, and γ_k. α represents a constant term and e is the usual error term. Utilization, U in model (AV.1) represents *NIC* per *ASTRO(97)-PU*.

The results of estimating model (AV.1) may be interpreted in the following manner. The estimated coefficients attached to the needs variables represent the additional amount of spend in terms of *NIC* per ASTRO(97)-*PU* resulting from a one unit increase in the needs variable. The coefficient α, whose magnitude is also estimated from the data, represents the average *NIC* per *ASTRO(97)-PU* across the total population of practices and hence measures the average age, gender and temporary resident adjusted spend on prescriptions per capita in a year.

Model (AV.1) contains the set of *n* supply variables to control for the influence that supply may have on the estimated coefficients of need (thereby adjusting for correlations between supply and need) and to obtain good model specification (robust model fit).

Multiplicative model specification

The alternative functional form is a multiplicative model of utilization which is specified as follows:

$$U = \alpha \prod_{j=1}^{m} N_j^{\beta_j} \prod_{k=1}^{n} S_k^{\gamma_k} \qquad \text{(AV.2)}$$

In order to make this model operational for estimation, the natural logarithm of all variables must be taken. This gives:

$$\log U = \lambda + \sum_{j=1}^{m} \beta_j \log N_j + \sum_{k=1}^{n} \gamma_k \log S_k + \varepsilon \qquad \text{(AV.3)}$$

where $\lambda = \log \alpha$.

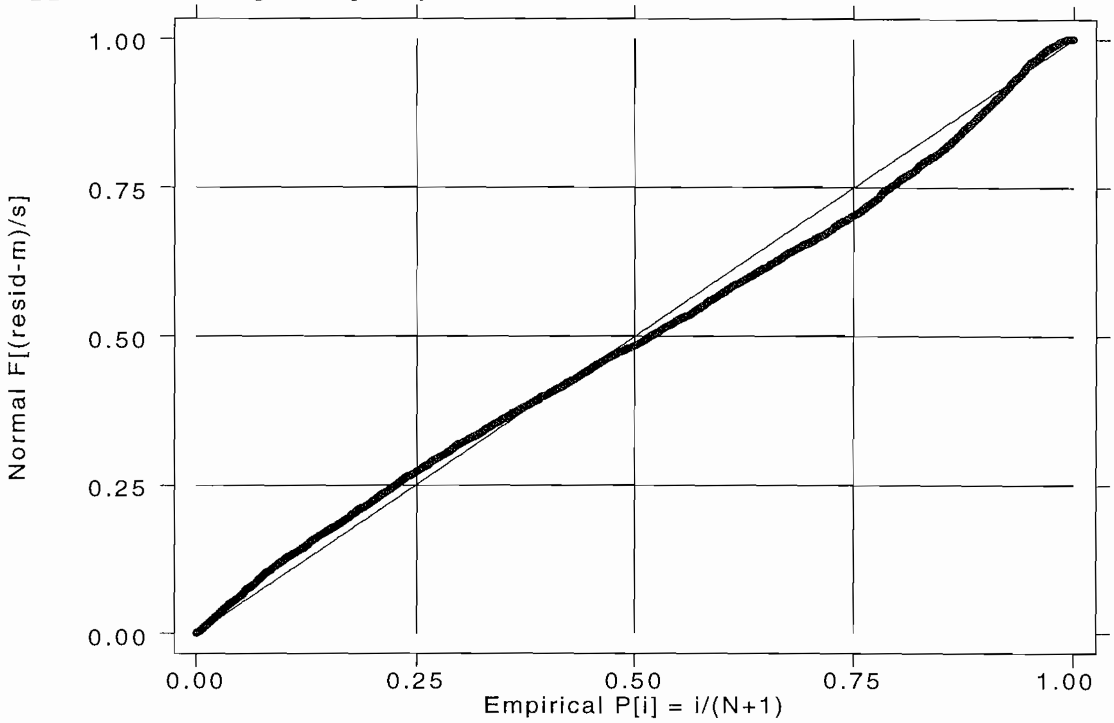
If the multiplicative model is chosen, then the estimated parameters β_j satisfy the relationship:

$$\beta_j = \frac{N_j}{U} \times \frac{\delta U}{\delta N} \qquad \text{(AV.4)}$$

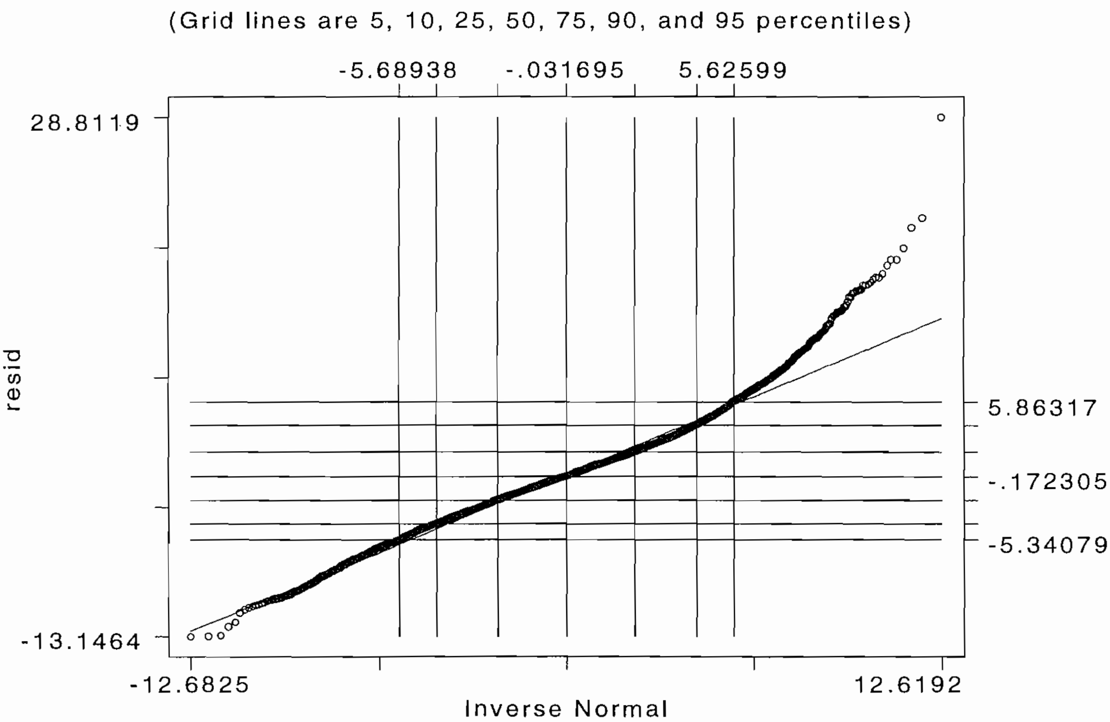
That is, the coefficient of $\log N_j$ indicates the elasticity of utilization with respect to the needs variable N_j. It can be interpreted as the percentage increase in utilization brought about by a 1% increase in need, N_j. Similarly for supply.

In the absence of any particular over-riding theoretical justification for the elimination of one of the two specifications, the choice of which to use is largely an empirical issue to be determined by the data. In the work presented here, both linear and multiplicative models were tested.

Appendix VI: *Diagnostic plots for model.*



Normal probability plot for residuals of model: cost/astro(97)-pu against ppsick pnocare1 pstudent and perc. babies plus supply.



Quantile probability plot for residuals of model: cost/astro(97)-pu against ppsick pnocare1 pstudent and perc. babies plus supply.