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MODELLING WAITING TIMES FOR ELECTIVE SURGERY

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SUMMARY

This study models NHS waiting times for elective surgery as if they were a "price" to the patient for receiving the procedure. This insight allows us to build a model of the demand for and supply of elective surgery along the lines of the conventional supply and demand model developed by economists. On the demand side, a high waiting time may deter use of NHS elective facilities, perhaps because the patient decides to seek private health care, or because the patient seeks an alternative to surgery, or because the patient is admitted as an emergency. On the supply side, because of local political pressure, a high waiting time may induce increased provision of NHS resources, or increased efficiency, or increased intensity with which those resources are used.

These considerations are modelled in this study using conventional econometric techniques. Waiting times and numbers of operations are modelled in about 4,500 small areas covering the whole of England. Data for the year 1991-92 forms the basis for the analysis. The model takes account of variations in need and variations in NHS supply across the country. A separate equation is estimated for each component of the model.

The results are statistically satisfactory, and appear plausible. They suggest that - on the demand side - long waiting times act only as a very modest deterrent to demand for surgery, except perhaps in areas currently experiencing relatively long waits. This implies that waiting time may not be an important component in medical referral patterns, except where waiting times are exceptionally long. On the supply side, however, there is a very strong positive relationship between the local waiting time and numbers of operations, suggesting that long waiting times act as an important stimulus to more intensive use of NHS resources.

The results are used to infer the policy implications of an increase in resources devoted to NHS elective surgery, assuming current medical technology and popular expectations remain in force. They indicate that increased resources would result in reductions in waiting times, and that the induced demand arising from lower waiting times would be relatively trivial. However, the reductions in waiting time would clearly take some time to materialize, and the results are dependent on the resource increases being permanent.

PREFACE

This report documents the findings of a statistical analysis of the determinants of waiting times for NHS routine surgery in small areas in England. This work, undertaken at the University of York, was commissioned by the NHS Executive. The report is divided into two parts. The first describes the study in its entirety, but omits much of the technical detail. The second part contains the technical details of the study. We should like to thank Keith Derbyshire, Jeremy Hurst, Pam Murphy, and Geoff Royston of the NHS Executive for their helpful guidance during the course of the study. Our thanks are also due to Ann van Ackere at the London Business School, Diane Dawson at Cambridge University and Dave Worthington at Lancaster University for helpful advice. Finally, we gratefully acknowledge invaluable advice and support provided by John Hutton, Andrew Jones, Chris Orme, Alan Williams and other colleagues at the University of York.

MODELLING WAITING TIMES FOR ELECTIVE SURGERY

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PART I

The report is arranged in two parts. Part I describes the main features of the study, and gives summary empirical results. Part II contains details of the analysis. The outline of Part I is as follows. Section 1 gives the background to the study. Section 2 develops the model that we have used, which is analogous to a standard economic model of supply and demand. Section 3 describes the data that were available for the study, and gives some rudimentary descriptive statistics. Section 4 describes the empirical estimation of the model, and Section 5 examines the policy implications of the work.

1. BACKGROUND

Throughout the first 25 years of the NHS there were, at any point in time, about half a million people waiting for hospital treatment in England. Over the next two decades this figure doubled, and waiting times have become a subject of great public concern. Partly in response to this concern, the Government has launched various initiatives to reduce the time that patients have to wait for treatment, most recently in the Patient's Charter. However, despite considerable political, professional, and public interest, our understanding of the determinants of waiting times remains poorly developed (Pope, 1992).

In this study, in common with most commentators, we focus on waiting times for elective surgery. These are a complex phenomenon, being a function of numerous interlinked factors. It has rarely been possible to undertake empirical work within a coherent theoretical framework that permits simultaneous modelling of all the major determinants of waiting times. Usually, analysis of the phenomenon has been confined to unrealistically simple models, or of piecemeal examination of variables thought relevant to waiting times. It has hitherto proved impossible to examine the impact of one particular factor on waiting times while holding all other factors constant (see, for example, Yates, 1987).

It might reasonably be assumed that the length of waiting time is related to the adequacy of resources for treatment (Sanderson, 1982). Indeed, in comparison with many other industrialized countries, the UK spends a relatively small proportion of its GDP on health (Yates, 1987, pp.30-31). However, claims that there is no straightforward relationship between resource provision and waiting times abound (for example, Frankel, 1989; Buttery and Snaith, 1979). Unfortunately, this view is usually based on simple correlations between some measure of inpatient provision and waiting times. For example, Buttery and Snaith concluded that "waiting lists are not correlated with surgical provision" (Buttery and Snaith, 1980, p.57) and Yates found "...no obvious relationship between a shortage of beds and long waiting time" (Yates, 1987, p.35).

Findings such as these can be interpreted as evidence that increased funding would have little impact on waiting times and that more resources would simply induce greater demand (Pope, 1992; Roland and Morris, 1988). Indeed, some studies have found no simple relationship between admissions from the waiting list and the length of the list (Goldacre *et al.*, 1987; Henderson *et al.*, 1995), although other studies suggest that the pool of unmet need might be smaller than previous estimates suggested (Williams *et al.*, 1994). The common feature of all these studies is that - usually because of data limitations - they fail to model the system as a whole.

Drawing on a comprehensive and previously unavailable dataset, this report seeks to contribute to the debate by modelling the interactions between factors relevant to waiting times. It constructs a model of the determinants of waiting times based on the demand for and supply of NHS inpatient health care. This framework permits us to move towards a more comprehensive analysis, in which the links between resource levels, utilization rates and delayed access to health care can be modelled (Frankel, 1993, p.45). Although the model we present can be used to analyze the direct impact that an increase in provision is likely to have on waiting times, it can also be used to estimate the magnitude of any indirect demand effect induced by reduced waiting times.

2. THE MODEL

In this Section of the paper, we develop the theoretical model of elective surgical utilization with which we intend to analyze the waiting time phenomenon. Throughout, by waiting time we mean the time that elapses between the decision to admit for an elective surgical procedure and the actual admission date. Our discussion therefore does not refer to emergency admissions, and does not consider the time waiting for an outpatient appointment.

In queuing theory, management scientists have well-developed models of waiting times (Worthington, 1987, 1991). In the simplest of all situations - a single server and a single queue - it can be shown that the average total time a person is waiting in the system is equal to $1/(\mu - \lambda)$, where λ is the arrival rate of new referrals and μ the service capacity (Shogan, 1988). This formula might at first seem excessively simple for the NHS situation, in which a large number of queues with different needs are served by a multiplicity of hospitals. However, it is at times helpful to think of the NHS system *as a whole* as a single server with a single (albeit heterogeneous) queue. In these circumstances the insights of queuing theory may be useful, in the sense that they highlight the vital importance of two aspects of any queue in determining waiting times: the *supply* side (service capacity μ), and the *demand* side (arrival rate λ). Nevertheless, the standard queuing model has serious shortcomings, of which the most important is the assumption that μ and λ are fixed, remaining unchanged whatever the length of the queue. This paper seeks to model explicitly the possibility that these two components of NHS queues may depend on waiting times.

Throughout, we think of waiting time as being analogous to the price that must be paid to gain access to inpatient surgery, along the lines suggested by Lindsay and Feigenbaum (1984). Like any price, it is likely to influence demand for NHS procedures. However, in this guise, waiting time may also act as a signal to suppliers that more resources should be allocated to a particular activity. Hence waiting times are also likely to influence supply. To complicate matters, an increase in supply may stimulate increased demand (via a reduced waiting time) and thus the net effect on waiting times is unpredictable.

We assume that the quantity of health care delivered is some measure of utilization of NHS surgical resources. Then, to disentangle the effects of changes in demand and supply on waiting times, it is necessary to consider demand and supply separately. This gives rise to a simultaneous equation system incorporating both a demand curve and a supply curve. The two equations can then be solved to examine the overall impact on waiting times and utilization of, say, an increase in supply. The purpose of this study is to offer a comprehensive and robust empirical estimation of the basic model suggested by Lindsay and Feigenbaum.

An increase in the price of a good will usually reduce demand. Thus we might suppose that - other things being equal - an increase in waiting time will reduce surgical utilization. In response to an increase in waiting time, some people may seek private treatment, others may not be referred on to a consultant surgeon by their general practitioner (GP), and some who are referred may not be put onto the waiting list by the consultant. These issues have been raised by Cullis and Jones (1986) and formally modelled by Goddard, Malek and Tavakoli (1995). This study does not explicitly distinguish between the various processes whereby demand for NHS surgery may be suppressed. Instead, it models the net effect of waiting times on all relevant decision-makers (patient, GP and consultant).

Of course, waiting time is not the only factor that will affect the demand for health services. Areas have different needs for health care and, in high need areas, it is to be anticipated that, other things being equal, there will be a higher level of utilization. In addition, the availability of potential substitutes for hospital utilization - in the form of private facilities - may influence NHS demand. Finally, the local supply of GPs may influence demand for surgery, although whether primary care acts as a substitute or complement for inpatient surgery is an empirical matter to be determined. Thus the demand equation we propose is of the form:

$$\begin{aligned} \textit{Utilization}_{\textit{demand}} = f\,(& \textit{waiting time } (-), \\ & \textit{need } (+), \\ & \textit{GP supply } (?), \\ & \textit{provision of private inpatient beds } (-)) \end{aligned}$$

The anticipated direction of each effect is indicated (in parentheses) after each variable.

On the supply side, utilization will be directly affected by the volume of the available

NHS resources (the number of beds) and the efficiency with which these resources are used. As will become evident in Section 2, measurement of the magnitude of local supply is fraught with difficulty, and heavily constrained by data availability. However, it is possible to envisage a number of useful practical indicators of the effective capacity of local health services. With regard to the volume of resources, an increase in the number of available inpatient beds is likely to facilitate greater utilization. We have available two indicators of inpatient surgical provision:

(i) the total provision of acute inpatient beds, and
(ii) the proportion of surgical admissions that are elective.

The first of these phenomena gives a global indication of the level of local NHS inpatient capacity. The second is a more specific indication of the proportion of resources devoted to elective surgery. However, it is in practice problematic because it may be depressed if emergency admissions have been used to circumvent waiting lists. Therefore the impact of this phenomenon on utilization is difficult to predict. However, we feel it is likely to be an important part of any model of elective surgical admissions.

As well as influencing the total provision of resources, long waiting times may induce increased capacity as policy-makers seek to cut waiting lists through making better use of existing resources. A more efficient utilization of fixed resources can be thought of as equivalent to a larger volume of such resources. Two indicators of efficiency are:

(i) the proportion of all elective surgery that is done as day cases; and
(ii) the average length of stay in hospital of elective surgical cases.

As the second indicator of efficiency incorporates day cases (with a zero length of stay), there will be some overlap between these two measures and thus there might be some difficulty disentangling the impact of these two variables. In using these process variables as efficiency indicators, we are not suggesting that indiscriminate use of day cases and reductions in length of stay are necessarily effective, either for the NHS or for the patient.

The complete supply equation proposed in this report is therefore:

$$
\begin{aligned}
\textit{Utilization}_{supply} = g\,(\; & \textit{waiting time } (+), \\
& \textit{provision of NHS beds } (+), \\
& \textit{share of elective surgery done as day cases}(+), \\
& \textit{length of stay in hospital } (-), \\
& \textit{proportion of admissions that are elective } (?)).
\end{aligned}
$$

Of course, the resource and efficiency variables might themselves be influenced by waiting times and this is a matter we return to below.

The demand and supply equations give the *desired* level of utilization under various circumstances from the perspective of, respectively, patients and the NHS. In practice, of course, the two levels of utilization must coincide. That is, we must impose the market clearing condition that:

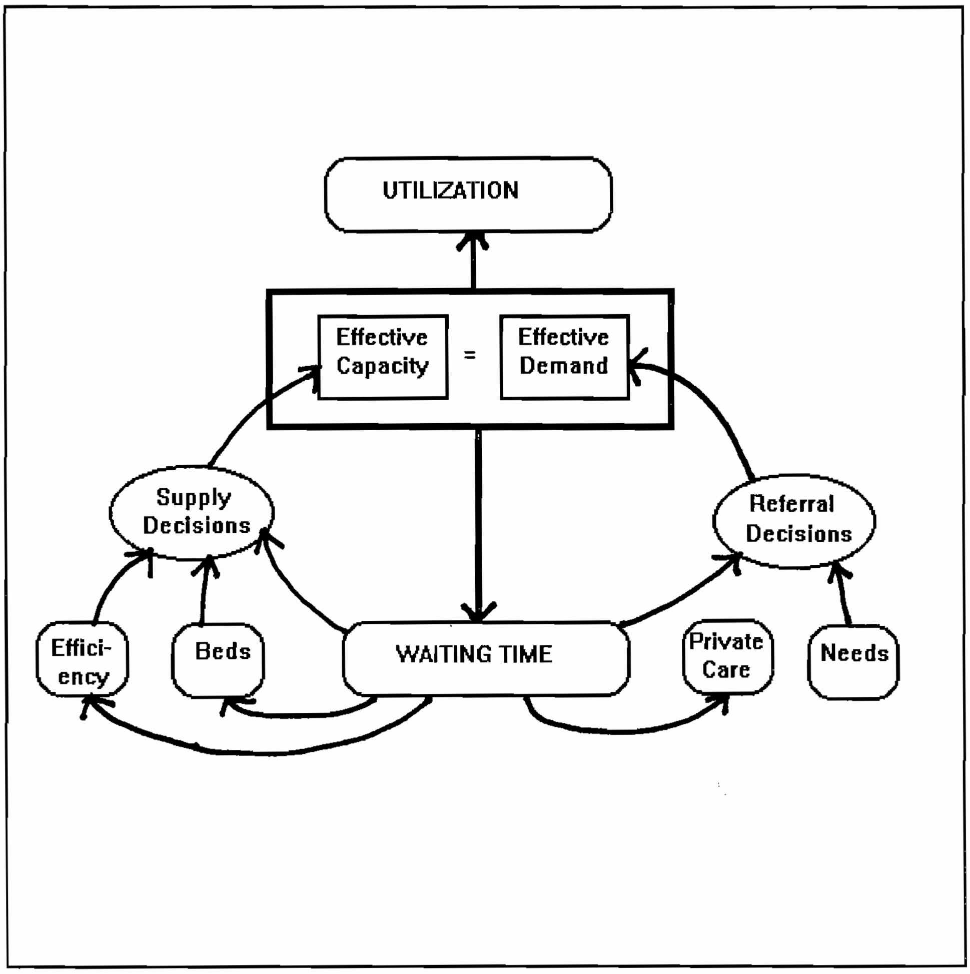
$$\textit{Utilization} = \textit{utilization}_{demand} = \textit{utilization}_{supply}$$

This is simply an accounting identity stating that observed supply equals observed demand.

The model we have developed above can be summarized in diagrammatic form, as illustrated in Figure 1. The central box represents NHS facilities for elective inpatient surgery. The *effective capacity* of the system can be thought of as the queuing theory service capacity μ, while the *effective demand* can be thought of as the arrival rate λ. These give rise to a waiting time. This in turn influences the referral decisions made by GPs, consultants and the patients themselves on the demand side, and decisions about resource provision on the supply side. If waiting times become high, the system may provide a signal to GPs or consultants to refer fewer patients, or to patients to seek private treatment. Simultaneously, it may indicate to policy-makers that they should provide more resources, or that they should use existing resources more intensively. All these responses will serve to bring down waiting times.

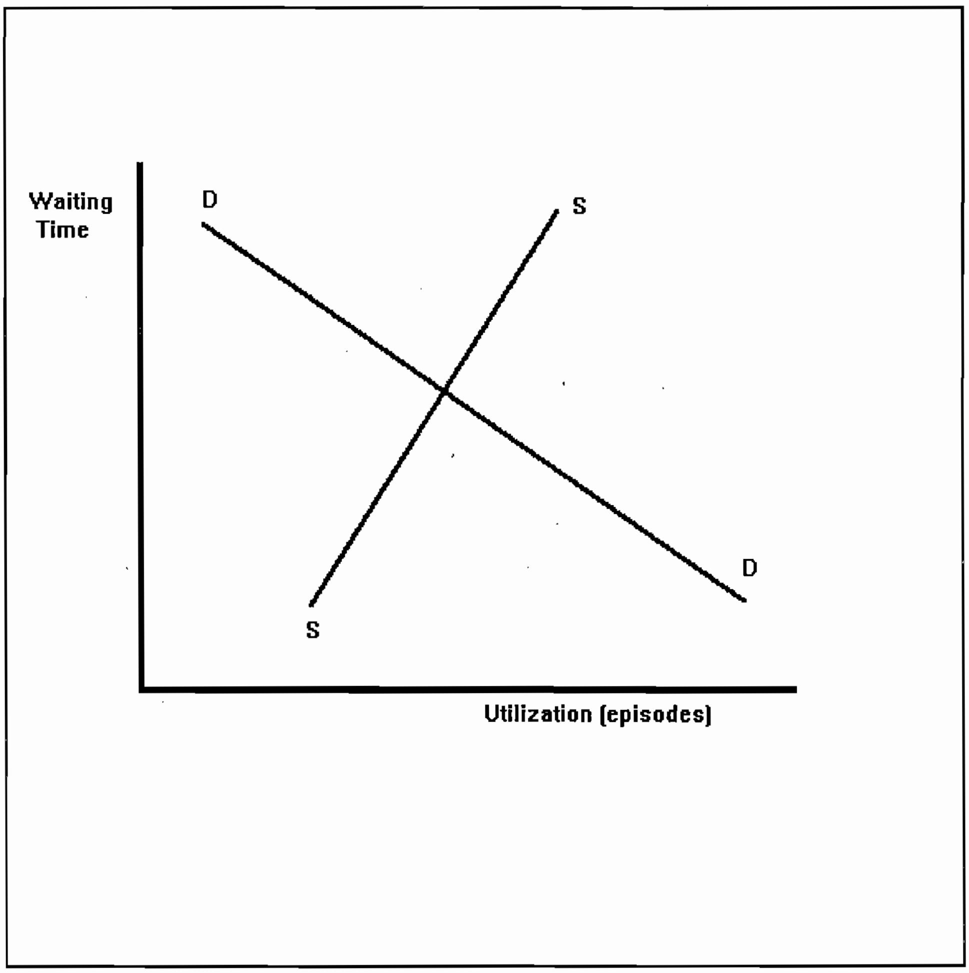
Notice therefore that we assume that many of the variables in the model are affected to some extent by waiting times: the provision of NHS beds, process and efficiency variables, and the provision of private beds. In the econometrician's jargon, these variables are therefore considered "endogenous" to the system. There may be many influences on these variables other than waiting time: for example, the overall provision of NHS resources. However, only the needs of the population are considered to be truly exogenous to the system we have sketched.

Figure 1: The model of elective NHS surgical care



Fundamental to our analysis is the assumption that the system has reached some sort of equilibrium. That is, GPs and policy makers have had a chance to observe local waiting times - perhaps over an extended period of time - and have adjusted their referral decisions and resource allocation decisions accordingly. The amount of discretion on either the demand side or the supply side may be limited: for example, population needs may be such that the scope for suppressing demand may be limited; and resource or clinical constraints may preclude major changes in supply. However, some sort of accommodation between the sides must be reached, and we assume that this equilibrium is what we observe. If the system is more dynamic than this analysis suggests, then it may be necessary to examine the impact of *lagged* waiting times on decisions, and this is something we explore in Section 9.

Figure 2: The supply of and demand for elective NHS surgical care



Graphically, the supply and demand model might look something like that in Figure 2. The demand curve DD is drawn as downward sloping, because the demand for elective surgery is assumed to decline as the waiting time increases. The supply curve SS is drawn as upward sloping because - for a given level of resources and efficiency - waiting time can be expected to increase as the number of operations demanded increases. An increase in needs - other things being equal - shifts the demand curve outwards, while an increase in the volume of resources or the efficiency with which they are used shifts the supply curve outwards. The precise slope of the curves remains an empirical matter. However, if we can estimate the curves, we should be able to predict the impact on utilization and waiting times of a shift in resources.

When it comes to empirical estimation, we shall be using over 4,500 small areas as the unit of observation (see Section 3). It is important to bear in mind, therefore, that we shall be modelling the impact of waiting times at a very local level, and that for each small area we are likely to observe a different equilibrium, depending on local needs, resources and random fluctuation. Thus the *observed* link between utilization and waiting times is likely to be a superficially incomprehensible jumble of demand and supply effects. This is why piecemeal examination of correlations between variables can be misleading. Our task is to disentangle the effects so as to isolate the impact of supply and demand changes on waiting times. The next Section describes the data that will be used for this purpose.

3. THE DATASET

Full details of the data used in this study, and associated descriptive statistics are given in Section 8 of Part II. This Section outlines the main features of the data.

The principal dataset on which this study is based is the Hospital Episode Statistics (HES) system, an annual database of hospital inpatient activity in England, including day cases. We were supplied with data from the two financial years 1990-91 and 1991-92. Our extract contained the following information of relevance to this study:

method of admission (emergency/booked/waiting list/planned)
wait for elective admission
age group
sex
specialty group (routine surgery/gynaecology)
episode duration
district of treatment
synthetic ward (small area) of residence.

Most of these items are self explanatory. It should be noted that - for confidentiality reasons - we had access to only broad specialty groupings, of which only two were relevant to this study: routine surgery and gynaecology. Routine surgery comprises all surgical specialties except plastic surgery, cardiothoracic surgery, paediatric surgery and gynaecology.

One key data item from the perspective of this study is the "synthetic ward" in which the patient lives. The synthetic ward is the most specific indicator of area of residence that the Department of Health is prepared to release. There are 4,985 synthetic wards covering the whole of England, with average population about 10,000. This study uses these small areas as its units of observation.

The wait for elective admission is calculated as the number of days between a decision to admit a patient and his or her admission to hospital. The 1991-92 HES database, which is the one upon which we focus in most of our modelling work, consists of a total of 9,042,168 records. We discarded records that were in specialties other than surgery, which were emergency, or which were for other reasons not relevant to this study. In order to prevent the analysis being distorted by a few very long waits, we also excluded the very small number of episodes with a wait of longer than 3 years. This left 2,252,192 valid records for elective episodes in routine surgery or gynaecology.

The average wait across England was 106.7 days, but there were considerable variations across the country, with an average of 85.3 days for those treated in Northern Region and 127.2 in South West Region. (Throughout this report we use the 14 former Regional Health Authorities, and the District Health Authorities that existed in April 1992). The distributions of waiting times also varied considerably between Regions, with for example 71.5% of cases being admitted within 3 months in Northern, compared with only 60.7% in South West. Variations within Regions are even greater.

We also explored variations in waiting times between age and sex groups, but found little variability, other than amongst the very young. Those aged under 1 year had an average wait of 41 days.

We constructed three indices of waiting time for each small area:

(a) the average waiting time;
(b) the proportion waiting longer than three months;
(c) the standardized waiting time.

This last variable is defined as the ratio of *actual* waiting times in the ward to *expected* waiting times. Expectations are based on the national average wait, given the patient's age, sex and specialty group. Given the nature of the dataset made available to us, this variable represented the only way in which we were able to make some allowance for differences in case mix between areas. The variables were constructed for routine surgery alone, gynaecology alone, and the two specialty groups combined. In practice, we found that the three definitions yielded very similar results. For example, in routine surgery, the standardized wait has a correlation of 0.999 with the average wait, and both these variables have a correlation of 0.883 with the proportion waiting longer than three months.

We had to make a choice about which waiting time variable to focus on in the analysis, and we chose to use the standardized waiting time for routine surgery. We did however consider the alternative possible definitions in a sensitivity analysis.

As explained in Section 2, the purpose of this study is to model waiting times and hospital utilization as a function of various supply factors, such as efficiency and provision of inpatient beds, and various demand factors, such as socio-economic conditions. In order to make the model operational a number of other variables were derived for each small area from the HES dataset.

Hospital utilization was measured as the ratio of the actual number of elective surgical admissions in the small area as a proportion of expected admissions, given its population size and its age and sex profile. This variable therefore indicates the extent to which local utilization exceeds (or falls short of) national average levels. In routine surgery it is negatively correlated with average waiting times (ρ = -0.20).

In order to model supply considerations, a number of inpatient process variables were extracted as follows:

- the mean length of stay of all elective surgical admissions;
- the proportion of elective surgical admissions that were day cases;
- the proportion of all surgical admissions that were elective.

The first two of these variables are strongly negatively correlated. The third is intended to indicate the proportion of local inpatient surgical facilities devoted to elective procedures.

To complete the modelling work we also needed to draw on data from outside the HES. These related to the local supply of health care facilities, and the local demand for health care. The problem of deriving measures of the quantity of health care supply is that it is necessary simultaneously to reconcile the magnitude of facilities, their proximity to the ward of interest, and the impact of competing populations and competing supply. We were fortunate that - as part of an earlier study - we had available three measures of the *supply* of local health care facilities, referring to NHS acute inpatient provision, private inpatient provision, and GP supply (Carr-Hill *et al.*, 1994). These were derived using the methods of spatial interaction modelling, full details of which can be found in Appendix 1.

As an indicator of the magnitude of inpatient provision, we used the number of available acute beds. For each ward, access to these beds was measured by weighting each hospital by the distance from the ward. Similarly, populations were weighted by the distance to hospitals. The outcome is an access measure which is effectively the ratio of acute beds (weighted by distance from the ward) to population (again weighted by distance): in other words, an adapted version of the familiar "beds per head" ratio. Supply of general practitioners was calculated in a similar way, except that the numerator used was the number of general practitioners (weighted by distance to the surgery). Provision of private in-patient care was similarly calculated, using the number of visitors present on Census night in private hospitals as a measure of the magnitude of private inpatient supply. Average waiting times are strongly negatively correlated with the NHS inpatient supply variable ($\rho = -0.46$). There is also a negative correlation, albeit weaker, with GP supply and private supply.

Demand for inpatient surgery was assumed to be driven by clinical needs, which are not directly measurable. However, we had available for each ward a wide range of health and socio-economic data which could be considered plausible indicators of need. These data were drawn from the 1991 Census of Population and routine statistical sources. In summary they covered:

Mortality (various standardized mortality ratios)
Morbidity (limiting long-standing illness)
Housing Tenure
Housing Amenities
Car ownership
Overcrowding
Ethnic origin
Elderly living alone
Lone parents
Students
Migrants
Unemployment
Educational qualifications
Social class
Non-earning households

One particularly important needs indicator used in the study was the index for acute sector needs developed at the University of York, and now used as the basis for allocating acute NHS Hospital and Community Health Service funds (NHS Executive, 1994). The components of this needs index are as follows:

- the proportion of pensionable age living alone;
- the proportion of dependants in single carer households;
- the proportion of economically active unemployed;
- the standardized mortality ratio for ages 0-74;
- the standardized illness ratio for ages 0-74.

4. ESTIMATION

This Section describes how we made the model described in Section 1 operational using the data described above.

The demand side was estimated by modelling utilization as a function of waiting time, acute sector needs, and the availability of other health care facilities - namely, general practitioners and private inpatient care. Following the usual convention, the supply side was estimated by taking waiting times to the left hand side of the supply equation, and modelling them as a function of supply and resources. The variables entered into the supply equation were provision of NHS beds, the proportion of surgical admissions that were elective, and the two efficiency variables (day cases and length of stay).

As reflected in Figure 1, the needs variable was considered exogenous, or external to the system. However, because it is determined jointly by supply and demand equations, waiting time must be considered an endogenous variable. In addition, Figure 1 indicates that most of the other variables in this system are likely to be endogenous, in the sense that they are determined within the system. Thus in principle we should also write down an equation for each of the remaining variables. In practice, this is unrealistic, given the infeasibility of modelling the numerous other determinants of a variable such as NHS bed provision which lie outside our system. Instead, therefore, we focused on subsidiary equations for only three of the process variables: the proportion of surgical cases that are elective; the proportion of elective admissions that are day cases; and the average length of stay in elective surgery. These are assumed to depend on waiting times, supply variables, and needs variables.

Having determined the variables to include in the model, the next task was to decide on the precise functional form of the various equations underlying the model. In the light of earlier experience with data of this sort, we used the natural logarithms of all variables throughout. After deleting wards using the criteria set out in Section 3, a total of 4,460 observations were available. Each observation was weighted in proportion to the number of elective episodes in 1991-92. Regional dummies were included in the supply equation but are not reported.

Because of the endogeneity of variables, ordinary least squares regression methods were inappropriate, and two-stage least squares (2SLS) methods were therefore used to estimate all equations. In order to implement two stage least squares, it is necessary to specify a range of "instruments" with which to model the endogenous variables. We were fortunate in having available a wide range of potential instruments based on the socio-economic data described in Section 3, and we found it possible to specify a satisfactory set of instruments for each equation. We began by including all variables which we considered would be uncorrelated with the error term in the 2SLS regression equation, and then dropped the instruments which most clearly violated this assumption. At this stage, consideration was given as to whether the deleted instrument belonged in the equation as an explanatory variable. Again following standard econometric practice, in the 1991-92 model waiting time was instrumented using its own lagged values. Full details of the precise instrument set for each equation can be found in Appendix 3.

The chosen utilization measure was based on the number of elective surgical episodes, standardized for the ward's demographic profile. The length of stay and waiting time variables were also standardized for the age, sex and specialty of the episode. This removed the need to include age and sex variables in the demand and supply equations. Episodes in the gynaecology specialty were omitted from the analysis. This was because it was felt that the determinants of demand for and supply of gynaecological services might differ from those for routine surgery. The results presented here therefore relate only to routine surgery, by far the largest aspect of elective surgical admissions. The specification of all equations was tested carefully, using a conventional Sargan test statistic (Godfrey, 1988, p172). It was also possible to test whether variables were indeed endogenous

(Godfrey, 1988, pp192-194). In all cases this was found to be the case.

For both the demand and supply equations we obtained good, convincing results. The estimated 2SLS demand equation, which shows no evidence of misspecification, is reported in Table 1.

Table 1: The demand equation - the basic model

Dependent variable: utilization in routine surgery

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	4	56.20737	14.051842
Residuals	4455	152.40549	.034210

F = 410.78557 Signif F = .0000

------------------Variables in the Equation------------------

Variable	B	SE B	Beta	T
WAIT_TIME91	-.089138	.018466	-.097622	-4.827
GP_SUPPLY	-.107345	.027113	-.123480	-3.959
PRIV_BEDS	-.091535	.011525	-.264679	-7.942
NEED	.799958	.028973	.532100	27.611
(Constant)	-1.538794	.053461		-28.784

Misspecification test statistic = 0.62/(152.4/4456)= 18.1 $\chi^2_{.001}(12)$=32.6

Key:

WAIT_TIME91	Standardized waiting times for elective surgery, 1991-92
GP_SUPPLY	GP supply
PRIV_BEDS	Provision of private hospital beds
NEED	Weighted index of acute health needs (the York formula)

The needs variable is clearly significant and has a positive impact on demand. The waiting time variable is also significant and, has a weak negative effect. The provision of private hospital beds also have the anticipated negative impact on the demand for NHS in-patient services. It turns out that GP provision has a relatively weak negative impact on utilization, suggesting that GPs may act as a modest substitute for elective inpatient surgery. We explored further the deterrent effect of waiting times by estimating the model separately for the wards with the highest 1/3 waiting times and those with the lowest 1/3 times. We found that the coefficient in the "high" waiting time wards was substantially larger than that for the whole sample (a value of -0.30), while the coefficient in the "low" waiting time wards was insignificantly different from zero.

Table 2 reports the supply equation, again estimated using 2SLS. Like the demand result, this equation shows no evidence of misspecification. As anticipated, utilization is positively associated with waiting times, while increased provision of NHS beds appears significantly to reduce waiting times. The proportion of elective episodes that are treated as day cases has a significant negative impact on waiting times. The length of stay variable, which includes day cases with a zero stay, has a positive but statistically insignificant coefficient. The insignificance of this variable is not surprising given the high level of correlation between it and the day case variable (ρ = -0.66).

Table 2: The supply equation - the basic model

Dependent variable: waiting time for routine surgery

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	17	87.22271	5.1307477
Residuals	4442	140.47378	.0316240

F = 162.25529 Signif F = .0000

------------------Variables in the Equation------------------

Variable	B	SE B	Beta	T
UTLIZATION91	.355672	.033238	.324763	10.701
NHS_BEDS	-.256953	.013849	-.370522	-18.553
DAY_CASES	-.269184	.040026	-.261002	-6.725
LENGTH_STAY	.026908	.055536	.022471	.485
ELECTIVES	.114017	.039039	.078887	2.921
(Constant)	-.258089	.044442		-5.807

Misspecification test statistic = 1.49/(140.5/4443)= 47.1 $\chi^2_{.001}$ (31)=61.0

Key:

UTLIZATION91	Standardized utilization rate (episodes), 1991-92
NHS_BEDS	Provision of NHS beds
DAY_CASES	Proportion of all elective episodes that are day cases
LENGTH_STAY	Standardized (for age and sex) length of stay
ELECTIVES	Proportion of all surgical episodes that are electives

One attractive feature of the logarithmic models we have chosen to use is that the estimated coefficients measure the *elasticity* of the dependent variable with respect to the associated regressors. The elasticity is the percentage change in the dependent variable brought about by a one percent change in the regressor. For example, the estimated coefficient on the waiting time variable in the demand equation is -0.09. This implies that a 1% decrease in waiting times will be directly associated with a 0.09% increase in demand. Now a 20-day reduction in the mean waiting time of 100 days is equivalent to a cut of 20% and thus, in this situation, demand can be expected to increase by 0.09 multiplied by 20 = 1.8%. While this calculation is only a rough estimate, it does suggest very strongly that the induced demand effect of a substantial reduction in waiting times is rather small.

Although we were guided by economic and econometric theory when developing the demand and supply models reported above, a number of judgements had to be made. It was therefore important to examine the robustness of the model with respect to different assumptions. Consequently, the model was re-estimated so that we could examine the sensitivity of the results with respect to a range of alternative assumptions, as follows:

(a) omitting the length of stay variable from the supply equation;
(b) examining variations across the country;
(c) measuring utilization as the cost of episodes rather than the number of episodes;
(d) adding the gynaecology specialty to the analysis;
(e) measuring waiting time as the proportion of patients waiting longer than 90 days;
(f) measuring waiting time as the crude waiting time (rather than standardized waiting time);
(g) estimating the equations with ordinary least squares rather than two stage least squares.

The full results of the sensitivity analysis are reported in Section 10. On the whole, the results are remarkably robust to different assumptions. There is a tendency for the deterrent effect of waiting times to be higher in metropolitan areas and London. However, most aspects of the supply equations are remarkably stable. The one exception is the variable measuring the proportion of surgical admissions that are elective. The sign on this variable becomes negative in metropolitan areas, and we would suggest caution in interpreting its meaning.

Measuring utilization by the *costs* of episodes (rather than the number of episodes) has little impact on the results. When gynaecological episodes are added to the dataset, the significance of waiting times as a demand deterrent is much reduced, confirming the importance of treating this specialty separately. Measuring waiting time as either the proportion waiting longer than 30 days or the crude waiting time does not alter the broad conclusions, although some of the coefficients change in magnitude. The use of ordinary least squares methods does however lead to radically different coefficients, and emphasizes the importance of using the more appropriate two stage least squares methods employed in this study.

In short, although the sensitivity analysis did bring to light some variations in the details of the model, it did not produce any evidence which seriously compromises its general structure. As a result, we consider the equations reported above to represent a faithful representation of the link between waiting times and utilization on both supply and demand side.

Before examining the policy implications of the work, it was important to test whether waiting times themselves might be an important influence on some of the other endogenous variables, such as the day case variable, the length of stay, or the electives variable. This possibility was tested by developing separate equations for each of these variables, with waiting times as a potential explanatory variable in each. That is, we tested the hypothesis that waiting times might influence these supply variables. The results are reported in Section 11.

In summary, we found that waiting times appear to have little detectable influence on the day case proportion or the length of stay. We therefore assume that waiting times have no impact on either of these variables. However, we did find that they played an important part in influencing the proportion of surgical admissions that are elective.

A priori, the impact of waiting times on the proportion of all episodes that are elective admissions is difficult to predict. As waiting times increase, more patients might be admitted as emergencies yielding a negative relationship. Alternatively, as waiting times increase more resources might be devoted to reducing them, thus generating a positive relationship. It is also to be expected that, as the provision of NHS beds increases, so too will the proportion of all episodes that are elective, and the efficiency with which the available beds are used will also have a positive impact. To the extent that GPs undertake minor surgery and private hospitals offer substitutes for NHS treatment then the availability of both of these facilities may reduce the proportion of all episodes that are elective. In high need areas, patients are likely to be less able to wait for treatment than their counterparts in lower need areas. Hence high need areas are likely to have a lower proportion of admissions that are elective episodes. Thus our model, with predicted signs in parentheses, was as follows:

The proportion of all episodes that are elective	= f(	waiting times (?), the accessibility of NHS beds (+), the proportion of episodes that are day cases (+), the length of stay in hospital (-), GP accessibility (-), the accessibility of private hospital beds (-), social and health need (-)).

The equation we obtained, which shows no evidence of misspecification, is reported in Table 3, and is broadly consistent with our hypotheses. We found it necessary to add a further variable reflecting the proportion of residents aged 75+ in residential/nursing homes.

Table 3: Modelling the proportion of all admissions that are elective

Dependent variable: the proportion of all episodes that are elective

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	20	44.832650	2.2416325
Residuals	4441	94.022066	.0211714

F = 105.87577 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
WAIT_TIME91	.290907	.059514	.420456	4.888	.0000
NHS_BEDS	.210621	.040568	.438964	5.192	.0000
DAY_CASES	.148023	.033845	.207439	4.374	.0000
LENGTH_STAY	-.239845	.046249	-.289495	-5.186	.0000
GP_SUPPLY	-.056118	.023356	-.085192	-2.403	.0163
PRIV_BEDS	-.232496	.031174	-.887224	-7.458	.0000
NEED	-.195807	.026580	-.171885	-7.367	.0000
HOMES*	.119987	.032819	.054960	3.656	.0003
(Constant)	-.859743	.146893		-5.853	.0000

Misspecification test statistic = 1.22/(94/4442)=57.7 $\chi^2_{.001}$ (30)=59.7

Key:

WAIT_TIME91	Standardized waiting times for elective surgery, 1991-92
NHS_BEDS	Accessibility of NHS beds
DAY_CASES	Proportion of all elective episodes that are day cases
LENGTH_STAY	Standardized (for age and sex) length of stay
GP_SUPPLY	GP supply
PRIV_BEDS	Accessibility of private hospital beds
NEED	Weighted index of health needs
HOMES*	Proportion of residents aged 75+ *not* in residential/nursing homes

In the event, therefore, waiting time appears to have a strong positive impact on the proportion of surgical episodes admitted as elective. The remaining variables are statistically significant and have the expected sign.

5. POLICY IMPLICATIONS

The results described above can be used to infer predictions of the utilization rate and waiting time that will arise in an area, given its pattern of need and health care facilities. The supply and demand model (Tables 1 and 2) are combined with the equation modelling the proportion of elective admissions (Table 3) to yield a system of three equations. The three unknowns are utilization, waiting time and the elective variable. Expressions can therefore be derived for each of these variables in which the other two variables do not appear. The resulting equations for waiting time and utilization are as follows:

WAIT_TIME = -0.905 - 0.044 GP_SUPPLY - 0.059 PRIV_BEDS
+ 0.263 NEED - 0.233 NHS_BEDS - 0.252 DAY_CASES
- 0.000 LENGTH_STAY + 0.014 HOMES*

UTLIZATION= -1.458 + 0.021 NHS_BEDS + 0.022 DAY_CASES
+ 0.000 LENGTH_STAY - 0.103 GP_SUPPLY
- 0.086 PRIV_BEDS + 0.777 NEED - 0.001 HOMES*

where

WAIT_TIME	Standardized waiting times for elective surgery, 1991-92
UTLIZATION	Standardized utilization rate (episodes), 1991-92
DAY_CASES	Proportion of all elective episodes that are day cases
PRIV_BEDS	Provision of private hospital beds
GP_SUPPLY	GP supply
NHS_BEDS	Provision of NHS beds
NEED	Weighted index of health needs
LENGTH_STAY	Standardized (for age and sex) length of stay
HOMES*	Proportion of residents aged 75+ *not* in residential/nursing homes.

It is interesting to note that the coefficient on the NHS bed supply variable in the waiting time equation (-0.233) is little changed from that in the original supply equation (-0.257). Thus, the impact of increased resources on waiting times is strongly negative, even after allowing for the (small) impact of waiting time on demand, and its rather larger impact on supply (in the form of the proportion of admissions that are electives). Similarly, the day case variable is very important, and there is little difference between its direct impact on waiting times from the supply equation (coefficient = -0.269) and its impact when the full model is solved (coefficient = -0.253). Both GP supply and private inpatient provision reduce waiting times for NHS surgery, but these effects are much smaller than that associated with a change in the provision of NHS beds or use of day case surgery.

The utilization equation shows that the most important indicator of utilization is needs, as measured by the York acute sector needs index. The provision of NHS beds and the other health care variables have comparatively little influence on utilization. This is an interesting finding, in that it suggests - contrary to the belief of some commentators - that there is relatively little impact of health care supply on the demand for health care in England.

The policy implications of these results are therefore important. They suggest that increased NHS resources can bring about reductions in waiting times, and that the associated stimulation of demand is relatively trivial, except perhaps in areas currently suffering long waiting times. The other important finding is that increased use of day case surgery appears to have a strong negative impact on waiting times. Clearly the first of these variables - increase in NHS beds - is a policy instrument that can be readily influenced. However, the extent to which increased use can be made of day case surgery is dependent on clinical feasibility. For example, it may be the case that there is little scope for further day case work, given the current pattern of clinical need and the current state of medical technology.

These results contradict some of the received wisdom about waiting lists in the NHS. For example, they refute the claim that any increase in provision of surgical beds will necessarily result in increased demand, and therefore bring about little consequent improvement in waiting times. In seeking to understand our results, it is important to recognize that - although we have taken a snapshot of behaviour in just two years - we are observing a wide variety of different areas, with different levels of health care provision and clinical needs. We have shown the impact that these considerations have on utilization and waiting times in that year. However, as explained in Section 1, the assumption is that all areas are in equilibrium, and that therefore the equations we have estimated represent the *long run* link between supply and demand, given the state of medical technology in the years being studied. Thus, although we have estimated a cross-sectional model, the coefficients we have reported represent long run responses (Frost and Francis, 1979).

Therefore, in claiming that (say) an increase in beds leads to reduced waiting times, we imply that a *long run* increase in beds is required. In general, a short run boost to surgical provision to clear waiting times will not secure long run improvements in waiting times. This accords with the results of elementary queuing theory, which suggest that the long run average waiting time for service is simply a function of the arrival rate (λ)and the service capacity (μ). Only a permanent increase in capacity μ will reduce the long run waiting time, given a constant level of demand.

6. CONCLUSIONS

The purpose of this study was to model variations in waiting times for elective surgery at the small area level. On the demand side, the shortcomings of the HES data are well known. However, substantial efforts were made to clean the data and we feel confident that its worst deficiencies have been eliminated. We have sought to model supply side issues, such as the provision of NHS and private hospital beds using the best available data, but have to acknowledge that the complexity of these issues means that some of the variables used will necessarily offer only rough measurements of the phenomena we are seeking to capture. Nevertheless, we believe that the data available to us were far more comprehensive than any previously available.

There have been many other studies of waiting times. However, most have focused on one or two variables at a time. Consequently, the value of their results is questionable because these studies fail to model the complex interactions between variables. Waiting times are the product of complicated supply and demand mechanisms, and inferences based on simple univariate analysis can therefore be very misleading. By developing what we believe to be a rigorous and internally consistent model, we feel that our analysis can sensibly inform the debate about the determinants of waiting times.

It can be argued that - because of the dynamic nature of waiting lists - they should be modelled using time-series data, and that we should consider how waiting times in a particular area respond to changes in supply and demand through time. However, such a study is infeasible, given data limitations, and may in any case be fruitless, given the rapid changes in medical technology and popular expectations. Instead, the cross-sectional approach we have adopted offers a large number of observations of areas in different stages of development. It provides estimates of long run responses given current technology and demand characteristics, and this is probably the most useful information that can feasibly be provided for policy purposes. Moreover, the cross-section approach directly addresses the issue of why waiting times vary so considerably across the country. Although satisfying statistical rigour and being intuitively plausible, our basic model was subject to considerable sensitivity analysis. This battery of tests confirmed the robustness of our initial results. Contrary to the findings from some other studies, our results suggest that NHS inpatient provision has a significant negative impact on waiting times. Moreover, the induced demand effect following any reduction in waiting times is likely to be relatively small, particularly as waiting times start to fall. The Audit Commission (1990) noted that there was no empirical evidence to support the hypothesis that day surgery acts as a substitute for inpatient services, and so releases resources for use elsewhere. By showing that the proportion of elective admissions treated as day cases has a substantial negative effect on waiting times, our results suggest that such substitution may indeed be taking place. Identifying a separate effect for the length of stay proved much more difficult, not least because the day case and length of stay variables are highly correlated. This is an aspect of the present study that might repay further work.

Of course, changes in the NHS since 1991-92 may have modified the relationships that we have identified. However, the findings described here are robust to a large number of assumptions, and they are therefore likely to be broadly valid for the foreseeable future. This being the case, we would suggest that they offer policy makers a much more secure quantitative basis on which to base waiting list policy than has been available hitherto.

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PART II

In this part of the report we describe some of the issues raised in Part I in more detail. The four sections cover descriptive statistics, modelling results, sensitivity analysis, and the modelling of NHS process.

8. DESCRIPTIVE STATISTICS

This Section considers the data under five headings: a description of the dataset; regional variations in waiting times; demographic variations in waiting times; standardized waiting times; and correlation analysis.

8.1 The dataset

We were supplied with an extract from both the 1990-91 and 1991-92 Hospital Episode Statistics (HES). The principal analysis was undertaken using the 1991-92 data. HES is an annual database of hospital inpatient discharges and deaths. Our extract contained the following information for all finished consultant episodes:

method of admission
source of admission
wait for elective admission
age group
sex
specialty group
operation group (x4)
order number of episode
episode duration
discharge destination
district of treatment
synthetic ward of residence.

The wait for elective admission is derived from other information recorded in the database. It is calculated as the number of days between a decision to admit a patient and his or her admission to hospital. Three types of elective admission are distinguished: elective - waiting list; elective - booked; and elective - planned. Waiting list and booked admissions differ in that the latter are given a specific date for their admission when they are told that they require inpatient treatment. Planned admissions are those where another medical condition must be remedied before the patient can be admitted. If the need for this remedial treatment delays a patient's admission then it can be argued that planned elective admissions should not be included in our dataset. However, we feel that their inclusion is unlikely to be particularly significant as they comprise only a very small proportion of all elective admissions (in 1991-92, 3.5% of all surgical episodes were planned admissions).

The 1991-92 HES database consists of 9,042,168 records. Those relatively few records where the episode was ongoing, where the sex of the patient was recorded as neither male nor female, where the age of the patient was not recorded, or where the region of treatment was not meaningfully defined, were discarded. Of the remaining 8,762,746 episodes, just over 45% were allocated to routine surgery and gynaecology, and the distribution of these records across the former English Regional Health Authorities (RHAs) is shown in Table 1. Of these 3,964,355 records, two-thirds were classified as elective episodes and, of these elective episodes, just over 88% had a non-zero waiting time. The regional distribution of these elective episodes, and the corresponding episodes with a non-zero waiting time, are also shown in Table 1. (Similar data for 1990-91 can be found in Table A1 in Appendix 2.)

Table 1 Finished consultant episodes for routine surgery and gynaecology combined, 1991-92, by Region of treatment

RHA of treatment	Number of episodes	Number of electives	%	Number of electives with non-zero wait	%
Northern	312,214	192,926	61.8	172,039	89.2
Yorkshire	347,616	216,003	62.1	166,537	77.1
Trent	367,394	243,661	66.3	239,924	98.5
East Anglia	170,643	115,788	67.9	114,672	99.0
NW Thames	265,276	160,192	60.4	138,603	86.5
NE Thames	290,377	197,981	68.2	151,564	76.6
SE Thames	297,182	201,670	67.9	161,612	80.1
SW Thames	218,053	151,896	69.7	140,835	92.7
Wessex	228,275	159,800	70.0	116,273	72.8
Oxford	174,065	107,979	62.0	102,613	95.0
South West	256,502	184,470	71.9	183,520	99.5
West Midlands	374,822	253,899	67.7	211,819	83.4
Mersey	224,988	147,283	65.5	143,245	97.3
North West	403,314	287,557	71.3	265,835	92.4
SHAs	33,634	26,488	78.8	24,514	92.5
England	3,964,355	2,647,593	66.8	2,333,605	88.1

Preliminary investigation of the waiting time associated with those elective episodes from the 1991-92 HES with a non-zero waiting time revealed an average wait ranging from 87.9 days in Mersey region to 535.1 days in Yorkshire. Suspecting that the latter figure reflected a coding problem in the HES data set rather than reality, the mean waiting time was calculated for each Yorkshire District Health Authority (DHA). With the exception of two DHAs, this analysis revealed an average wait ranging from 73.8 to 144.2 days. Two DHAs (Calderdale and Huddersfield) has unrealistically long average waits (408.5 and 3507.0 days respectively), and so all episodes associated with these DHAs were excluded from the analysis. Examination of the mean waiting time associated with all other DHAs did not reveal any obvious outliers in 1991-92. However, a similar analysis of the previous year's HES (1990-91) revealed the need to exclude four further DHAs. One DHA in Northern region (Gateshead) had a mean waiting time of 20.2 days, one DHA in Trent (North Lincolnshire) reported an average waiting time of 348.8 days, and two DHAs in Yorkshire (Dewsbury and Leeds Western) both had a mean wait of 1.0 days. Records where treatment occurred in any of the six problematic DHAs were excluded from the analysis. Finally, all episodes where treatment occurred in a Special Health Authority (24,514 in 1991-92) were also omitted from the analysis. In an attempt to minimise any remaining errors due to the incorrect recording of waiting times, all records with a waiting time in excess of three years (8,832 in 1991-92) were also removed from the dataset. This left 2,252,192 records from the 1991-92 HES for further analysis.

8.2 Regional analysis of unadjusted waiting times

Waiting times vary considerably across the country. The data reported in Table 2 confirm this, revealing that the average waiting time for routine surgery and gynaecology in 1991-92 was almost 50% longer for treatment in South West RHA than in Northern RHA. The average wait across England as a whole was 106.7 days. Between 1990-91 and 1991-92, average waiting times increased in all Regions except North West, and there were particularly large increases in NW Thames (17.4 days) and South West Region (15.2 days). At the same time, most Regions witnessed an increase of about 10% in the number of episodes. The decline in episodes reported by NE Thames is more apparent than real, as it appears to have submitted two copies of one of its quarterly HES returns in 1990-91.

Table 2 Average waiting time (days) and number of episodes by RHA of treatment for routine surgery and gynaecology combined

RHA of treatment	Average wait (days)	Number of episodes	Average wait (days)	Number of episodes
	1991-1992		1990-1991	
Northern	85.3	171,443	84.0	153,356
Yorkshire	110.2	133,821	106.2	117,050
Trent	101.9	223,996	94.5	206,250
East Anglia	114.9	114,174	104.8	94,149
NW Thames	100.4	137,699	82.6	114,383
NE Thames	111.0	150,698	102.6	250,730
SE Thames	112.4	160,586	104.4	136,881
SW Thames	108.2	140,376	102.1	120,635
Wessex	115.0	115,948	111.7	102,954
Oxford	114.8	101,982	108.9	95,965
South West	127.2	182,374	112.8	160,625
West Midlands	114.5	210,076	110.6	197,053
Mersey	89.6	143,171	86.5	137,338
North West	98.2	265,158	104.3	243,608
England	106.7	2,252,192	101.2	2,130,977

In addition to the *average* waiting time in each area, policy-makers might also be interested in the distribution of such times. Hence the waiting time associated with each episode was allocated to one of six groups: 1-30 days; 31-90 days; 91-180 days; 181-365 days; 366-730 days; and 731-1095 days. Table 3 reports the percentage of episodes in each of these six groups by RHA of treatment for 1991-92. (Similar data for 1990-91 can be found in Table A2 in Appendix 2.) Thus 76,378 episodes in Northern region had a waiting time of between 1 and 30 days, representing 44.6% of all episodes in this RHA.

Table 3 Waiting time by RHA of treatment for routine surgery and gynaecology combined, 1991-92: percentage of episodes by length of wait

Row Pct RHA	Waiting time (days) 1-30	31-90	91-180	181-365	366-730	731-1095	Total Episodes
Northern	44.6	26.8	14.9	9.5	3.8	.5	171443
Yorkshire	38.5	27.8	14.9	11.2	6.4	1.2	133821
Trent	40.7	27.4	14.5	10.7	6.0	.7	223996
EastAnglia	37.5	27.7	15.3	11.6	6.6	1.5	114174
NW Thames	42.8	28.1	13.5	8.8	5.4	1.5	137699
NE Thames	37.3	28.5	15.2	11.7	6.0	1.3	150698
SE Thames	36.4	28.8	15.3	11.9	6.5	1.1	160586
SW Thames	37.4	29.4	14.9	11.1	6.1	1.1	140376
Wessex	31.9	30.6	17.2	13.7	5.5	1.0	115948
Oxford	34.8	30.6	15.4	11.3	6.3	1.5	101982
South West	35.4	25.5	15.5	14.0	8.2	1.4	182374
WestMidlan	33.8	30.9	15.2	12.5	6.4	1.1	210766
Mersey	39.7	30.0	15.0	10.9	4.2	.1	143171
North West	35.7	33.7	14.7	10.4	4.7	.8	265158
Total	37.6	29.1	15.0	11.3	5.8	1.0	2252192

Again, the picture of considerable geographical variation is confirmed. Over 44% of patients treated in Northern RHA waited less than one month while the comparable figure for Wessex was some 13 percentage points lower. Similarly, the percentage of episodes with a waiting time in excess of two years varied considerably across the Regions, from virtually zero in Mersey to 1.473% in North-West Thames. Data for all regions combined are reported in the last row of Table 3. These reveal that of the 2,252,192 episodes from the 1991-92 HES, 6.85% had a waiting time in excess of twelve months, while 1.01% (22,838) had been waiting longer than two years.

When modelling waiting times for elective surgery, the unit of analysis will be 4,985 small areas ("synthetic wards") with an average population of about 9,600. The HES extracts (for 1991-92 and 1990-91) supplied to us included a variable denoting the patient's synthetic ward of residence. By mapping each synthetic ward to a RHA, we were able to calculate the average waiting time by the patient's RHA of *residence*, as well as by the patient's RHA of treatment. This analysis reflects the purchasing (as opposed to providing) perspective adopted in this study. The results are reported in Table 4. (Similar data for 1990-91 can be found in Table A4 in Appendix 2.) Under the heading 'net inflow of episodes', we also report the difference between the number of episodes by RHA of *residence* and the number of episodes by RHA of *treatment*. For example, there were 10,561 more episodes where the patient was resident in Trent RHA than there were episodes undertaken in this Region. The average wait by RHA of treatment (Table 2) and by RHA of residence (Table 4) are very similar, although this is to be expected given the level of aggregation of the data.

Table 4 Mean waiting time by RHA of residence for routine surgery and gynaecology, 1991-92

RHA of residence	Average wait (days)	Rank	Number of episodes	Net inflow of episodes
Northern	85.4	1	172,066	623
Yorkshire	110.4	7	135,895	2,074
Trent	102.5	5	234,557	10,561
East Anglia	115.5	13	106,533	-7,641
NW Thames	102.1	4	143,697	5,998
NE Thames	110.7	8	143,304	-7,394
SE Thames	112.2	9	155,413	-5,173
SW Thames	108.5	6	147,636	7,260
Wessex	113.6	11	118,307	-5,641
Oxford	113.4	10	101,320	-662
South West	128.0	14	181,630	-744
West Midlands	114.3	12	209,796	-970
Mersey	89.6	2	146,749	3,578
North West	97.9	3	255,289	-9,869
England	106.7		2,252,192	n/a

NB If rank=1, RHA has shortest wait, if rank=14, RHA has longest wait.

This waiting time data can be presented at various levels of aggregation. One alternative that we have explored is to divide England into four areas: inner London, outer London, metropolitan areas, and non-metropolitan (shire) areas. Table 5 reports the mean waiting time for all routine surgery and gynaecology episodes in each of these four areas. Once more, substantial geographical variation is revealed, with patients resident in inner London waiting, on average, one month less than their counterparts in non-metropolitan areas. It is also noticeable that inner London waiting times increased by over 20% in 1991-92.

Table 5 Mean waiting time by area of residence for routine surgery and gynaecology combined

Area	Mean waiting time (days)	Number of episodes	Mean waiting time (days)	Number of episodes
	1991-1992		1990-1991	
Inner London	84.5	94,330	70.3	110,876
Outer London	101.0	183,949	97.0	185,184
Metropolitan	93.8	555,966	94.2	487,215
Non-metropolitan	114.0	1,417,947	106.8	1,347,702
England	106.7	2,252,192	101.2	2,130,977

In addition to the crude average waiting time, of some policy interest is the proportion of cases waiting longer than some threshold (such as, say, three months). Thus in addition to the mean waiting time, we also calculated the proportion of all episodes where the patient had waited longer than 90 days, by both RHA and area of residence. These results are shown in Table 6. The picture of substantial geographical variation is again confirmed, with the proportion of episodes waiting longer than 90 days in 1991-92 ranging from 28.5% in Northern Region to 39.3% in South West RHA. As is to be expected, those RHAs with a relatively long average waiting time also tend to have a relatively high proportion of episodes waiting longer than the chosen threshold. Similarly, RHAs with a relatively short waiting time have a relatively small proportion of cases waiting longer than the specified threshold.

Table 6 Proportion of routine surgery and gynaecology episodes waiting longer than 90 days by RHA and area of residence

Level of aggregation	Proportion of episodes waiting longer than 90 days (%)	
	1991-1992	1990-1991
(a) by RHA of residence		
Northern	28.5	27.9
Yorkshire	33.8	34.4
Trent	32.0	30.7
East Anglia	35.0	34.4
NW Thames	29.9	26.9
NE Thames	34.1	31.2
SE Thames	34.8	33.9
SW Thames	33.2	31.9
Wessex	37.0	36.2
Oxford	34.2	33.1
South West	39.3	36.6
West Midlands	35.3	35.0
Mersey	30.2	29.8
North West	30.6	31.8
(b) by area of residence		
Inner London	24.4	20.6
Outer London	31.0	30.1
Other metropolitan areas	29.5	30.0
Non-metropolitan areas	35.6	34.3
England	33.2	32.2

8.3 Demographic analysis of waiting times

Table 7 reports the average waiting time and the number of episodes by age and sex of the patient. (Similar data for 1990-91 can be found in Table A3 in Appendix 2.) Apart from the very young, there is little variation in the mean waiting time by age. For the young and the old, there is also little variation by sex, and the shorter wait for women of working age reflects the relatively short wait for gynaecology compared with routine surgery.

Table 7 Average waiting time (days) by age and sex for routine surgery and gynaecology combined, 1991-92

Mean Age	Males	Females	Both	Total Episodes
under 1	43.26	36.89	41.08	6326
1-4	98.15	89.25	95.09	80940
5-9	123.40	124.62	123.90	106110
10-14	109.42	118.82	114.05	56574
15-19	114.46	94.81	102.31	84461
20-24	122.17	91.51	102.14	140022
25-29	121.76	94.69	103.89	165830
30-34	119.55	100.06	106.65	166256
35-39	117.18	100.45	106.06	152556
40-44	113.12	96.42	101.79	161372
45-49	109.69	93.20	98.65	148187
50-54	108.47	90.27	97.24	134924
55-59	110.29	98.33	103.84	133287
60-64	110.11	101.79	106.02	144350
65-69	111.21	108.14	109.77	160868
70-74	109.25	114.72	111.83	149130
75-79	107.47	123.47	115.46	133073
80-84	109.10	130.62	120.77	84611
Over 85	110.14	135.21	125.92	43315
Total	112.22	102.56	106.70	2252192

8.4 Standardized waiting times

Neither the crude average waiting time nor the proportion of episodes treated within a given period make any allowance for case mix. The expected waiting time for surgery varies considerably depending on the urgency of the case, and ideally we should have wanted to have adjusted for case mix. However, for confidentiality reasons, detailed diagnosis data were not available to us. We therefore calculated the expected length of wait for each episode, given the patient's age, sex, and specialty group, using national average data (of the sort reported in Table 7). The third waiting time variable used in the analysis for a given small area was then the sum of the actual waiting times divided by the sum of the corresponding expected waiting times of all episodes originating from the area. This waiting time variable was therefore *standardized* for the age, sex, and specialty of each patient. It reflects the extent to which waiting times in an area exceed national average waiting times, given the pattern of episodes in that area.

Table 8 reports the standardized waiting time by RHA and area of residence. A value less than unity implies that the waiting times from an area were less than what would have been expected, given the age, sex, and specialty group of those episodes. Thus the total waiting time experienced by residents in Northern Region was some 20% below what they would have experienced had their waiting times been identical to the national average waiting time given their age, sex, and specialty groups. Similarly, patients resident in South West RHA waited, on average, 20% longer than the national average wait for their pattern of utilization.

Because the national average waiting times reported in Table 7 are, in general, fairly consistent between age/sex groups, this standardized waiting time variable is highly correlated with the two other waiting time variables that we have calculated. This is demonstrated by the fact that the rankings of the RHAs, in terms of their standardized and average waiting times, are very similar.

Table 8 Standardized waiting time for routine surgery and gynaecology combined by RHA and area of residence (1991-92)

Level of aggregation	Standardized waiting times			
	1991-92	Rank	1990-91	Rank
(a) by RHA of residence				
Northern	0.7994	1	0.8227	1
Yorkshire	1.0397	7	1.0499	10
Trent	0.9739	5	0.9578	4
East Anglia	1.0875	13	1.0474	9
NW Thames	0.9461	4	0.8298	2
NE Thames	1.0553	9	1.0452	8
SE Thames	1.0514	8	1.0416	7
SW Thames	1.0115	6	0.9968	5
Wessex	1.0606	10	1.0825	13
Oxford	1.0642	11	1.0724	11
South West	1.1933	14	1.1049	14
West Midlands	1.0658	12	1.0744	12
Mersey	0.8325	2	0.8668	3
North West	0.9150	3	1.0233	6
(b) by area of residence				
Inner London	0.8112		0.7275	
Outer London	0.9484		0.9629	
Other metropolitan areas	0.8794		0.9288	
Non-metropolitan areas	1.0641		1.0521	
England	1.0000		1.0000	

NB If rank=1, RHA has shortest wait, if rank=14, RHA has longest wait.

8.5 Correlation analysis

The suggestion that the three measures of waiting times are highly correlated can be more thoroughly examined by considering the degree of correlation at the synthetic ward level. We began with 4,985 small areas but this was reduced by about 10% to 4,460 through the need to exclude wards where the HES data, for a variety of reasons, were deemed to be unreliable. For example, in the modelling phase of this study we shall be using the length of stay in hospital as one indicator of inpatient efficiency. In Wessex Region, all day cases were given an episode duration figure of 1 day (rather than 0) in 1991-92 and this therefore necessitated the removal of all wards in Wessex RHA, as well as those where a non-trivial proportion (more than 10%) of all episodes were treated in Wessex. Also in the modelling work we shall be using a variable reflecting the utilization of inpatient services. Rugby DHA made no HES return in 1990-91 and hence we have excluded all wards in this District from the analysis.

Table 9 reports the correlation coefficients for the three measures of waiting time: (i) the mean wait (MWT); (ii) the proportion of patients waiting longer than 90 days (PLWEE), and (iii) the standardized wait (STWTE). These are subdivided into three specialty groupings: (i) routine surgery (specialty code R); (ii) gynaecology (specialty code G), and (iii) surgery and gynaecology combined (specialty code C). The Table reports 1991-92 data. (Similar results, based on 1990-91 data, can be found in Table A5 in the appendix.) A numeric suffix on a variable name denotes the specialty grouping and the year to which that variable refers. Thus MWTR91 is the mean waiting time for specialty R (routine surgery) for 1991-92.

For a given indicator of waiting times, there is a relatively low correlation (about 0.24) between the wait for surgery and the wait for gynaecology. However, the fact that there are relatively few gynaecology episodes means that there is a very high correlation (about 0.95) between the wait for surgery and the wait for surgery and gynaecology combined. There is also a remarkably high correlation between all three measures of waiting times. For example, the correlation coefficient between the crude average waiting time and the standardized measure of waiting time for routine surgery is 0.9992.

Table 9 Correlation coefficients between the three measures of waiting times for the three specialty groupings, 1991-92

	PLWEER91	PLWEEG91	PLWEEC91	STWTER91	STWTEG91	STWTEC91
PLWEER91	1.0000	.2663	.9377	.8828	.2697	.8727
PLWEEG91	.2663	1.0000	.5487	.1925	.8699	.4041
PLWEEC91	.9377	.5487	1.0000	.8080	.5115	.8776
STWTER91	.8828	.1925	.8080	1.0000	.2211	.9634
STWTEG91	.2697	.8699	.5115	.2211	1.0000	.4579
STWTEC91	.8727	.4041	.8776	.9634	.4579	1.0000
MWTR91	.8822	.1874	.8054	.9992	.2171	.9613
MWTG91	.2735	.8770	.5177	.2244	.9925	.4595
MWTC91	.8699	.4060	.8873	.9554	.4563	.9935

	MWTR91	MWTG91	MWT91
PLWEER91	.8822	.2735	.8699
PLWEEG91	.1874	.8770	.4060
PLWEEC91	.8054	.5177	.8873
STWTER91	.9992	.2244	.9554
STWTEG91	.2171	.9925	.4563
STWTEC91	.9613	.4595	.9935
MWTR91	1.0000	.2196	.9545
MWTG91	.2196	1.0000	.4620
MWTC91	.9545	.4620	1.0000

NB All correlations are statistically significant at the 1% level

Key:
PLWEER91 Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1991-92
STWTEG91 Standardized waiting time, specialty G (gynaecology) 1991-92
MWTC91 Mean waiting time, specialties R and G combined, 1991-92

Table 10 Correlation coefficients between waiting times 1991-92 and 1990-91

	PLWEER91	PLWEEG91	PLWEEC91	STWTER91	STWTEG91	STWTEC91
PLWEER90	.6639	.2849	.6588	.5952	.2927	.6174
PLWEEG90	.1816	.6126	.3573	.1187	.5944	.2670
PLWEEC90	.6128	.4549	.6864	.5277	.4511	.6030
STWTER90	.6077	.2415	.5880	.6214	.2513	.6266
STWTEG90	.1872	.5657	.3453	.1370	.6063	.2868
STWTEC90	.5923	.3774	.6249	.5890	.3951	.6385

NB All correlations are statistically significant at the 1% level

Key:
PLWEER91 Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1991-92
STWTEG91 Standardized waiting time, specialty G (gynaecology) 1991-92
MWTC91 Mean waiting time, specialties R and G combined, 1991-92

Table 10 reports the correlation coefficients between the two years' HES data for two measures of waiting times (the proportion of patients waiting more than 90 days and the standardized waiting time). Comparing the same specialty group in both years reveals a correlation coefficient of about 0.64. This confirms the picture from Table 8 that there is some movement in relative waiting times between the two years' data.

As explained in Part A, the process which determines waiting times is likely to be complex, and to require sensitive modelling. However, before beginning full development of a model of waiting times, it is instructive to consider the degree of correlation between all three measures of waiting times and those variables which are employed in the modelling work. These variables can be divided into four categories:

(a) indicators of the supply of health care;
(b) variables relating to the process and efficiency of inpatient services;
(c) measures of the demand for (utilization of) health care; and
(d) socio-economic and health variables reflecting the need for health care.

These are now considered in turn.

8.5.1 Supply variables

Of considerable policy interest is the impact that the supply of health care has on waiting times. As explained in Section 3, we developed three measures of supply relevant to this study, described more fully in Appendix 1. The variables are as follows:

NHS_BEDS	Provision of acute NHS beds in relation to population
GP_SUPPLY	Provision of GPs in relation to population
PRIV_BEDS	Provision of private hospital beds in relation to population.

Table 11 reports the correlation coefficients between the three waiting times variables (for 1991-92) and these three indicators of the supply of health care. (Similar results based on waiting times data for 1990-91 can be found in Table A6 in Appendix 2.) The results are similar irrespective of which waiting variable is used. As anticipated, there is a strong negative relation between the supply of NHS inpatient beds and waiting times.

Interestingly, this contrasts with the significant positive relationship between average daily available beds and the length of waiting list in 18 DHAs in Trent RHA in 1975 (Frost and Francis, 1979). However it agrees with a much earlier analysis by Culyer and Cullis (1975), who found a significant negative relationship between inpatient throughput capacity and waiting time in a study of English and Welsh Regions for the period 1962-71.

Increases in GP supply are also associated with shorter waiting times, perhaps reflecting the fact that some of the services provided by GPs/health centres can act as substitutes for those at a hospital. Frost and Francis (1979) found a positive but statistically insignificant correlation between the length of waiting lists and the number of unrestricted principals in general practice. Also intuitively plausible is the fact that increases in the availability of private health care beds tend to be associated with shorter waiting times - presumably by reducing the demand for NHS services.

Table 11 Correlation coefficients between the various measures of waiting times and the supply of health care, 1991-92

	NHS_BEDS	GP_SUPPLY	PRIV_BEDS
PLWEER91	-.4258	-.1311	-.1207
PLWEEG91	-.3007	-.1955	-.1726
PLWEEC91	-.4829	-.1906	-.1871
STWTER91	-.4094	-.1116	-.0272**
STWTEG91	-.2869	-.1571	-.1689
STWTEC91	-.4510	-.1440	-.0805
MWTR91	-.4020	-.1005	-.0186**
MWTG91	-.2988	-.1852	-.1691
MWTC91	-.4643	-.1559	-.0891

NB All correlations are statistically significant at the 1% level unless indicated with * (statistically significant at the 5% level) or a ** (not statistically significant at the 5% level).

Key:

PLWEER91	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1991-92
STWTEG91	Standardized waiting time, specialty G (gynaecology) 1991-92
MWTC91	Mean waiting time, specialty C (both specialties), 1991-92

8.5.2 Process variables

Having established a negative relationship between the supply of NHS facilities and waiting times, it is interesting to consider whether a similar relationship exists between waiting times and measures of process for NHS patients. Three process variables were constructed:

(a) the proportion of elective surgical admissions undertaken as day cases (PELDC);

(b) the average length of stay of elective surgical admissions (MLOSE); and

(c) the standardized (for age and sex) length of stay of all elective surgical admissions (STLSE).

These process variables could be construed as indicators of efficiency. However, they make no allowance for differences in case mix, and therefore any such interpretation should be treated with caution.

The fourth process variable relates to the proportion of surgical admissions that are elective. In interpreting this variable, it is important to bear in mind that two opposing factors may be at work. Where resources are particularly pressurized, it is possible that a relatively high proportion of those who have been waiting a relatively long time will be admitted as emergencies. In the HES system, such admissions do not have a waiting time and, because these episodes will tend to be those people that have been waiting a long time, the actual waiting time associated with all episodes in these areas may be artificially depressed. Alternatively, it could be that it is the most severe cases that are admitted as emergencies. Consequently, the remaining elective episodes are less severe, more able to wait, and thus have relatively long waiting times. In this case, the total waiting time associated with all episodes from an area will be artificially high. Although the anticipated impact of emergency admissions is unclear, this pheonomenon is considered a potentially important supply side variable, and is modelled by:

(d) the number of elective admissions as a proportion of all admissions in surgery (PADEL).

Table 12 reports the correlation coefficients between the three waiting times variables (for 1991-92) and the four variables relating to hospital processes. (Similar results, based on

1990-91 data, can be found in Table A7 in Appendix 2.) As expected, these statistics confirm the hypothesis that there is a negative relationship between waiting times and the proportion of elective episodes that are treated as day cases. This effect is more pronounced in surgery than gynaecology but is consistent across all three indicators of waiting time.

The second and third indicators of hospital efficiency - the average and standardized length of stay in hospital for elective episodes - are positively associated with waiting times. However, the correlations are relatively weak. Finally, there is some evidence of a negative relationship between waiting times and the use of emergency admissions as a mode of entry to inpatient services.

Table 12 Correlation coefficients between the various measures of waiting times (1991-92) and inpatient process variables

	PELDC191	PELDC991	PELDC91	STLSER91	STLSEG91	STLSEC91
PLWEER91	-.3133	-.1378	-.2996	.1361	.0428	.1391
PLWEEG91	-.1253	-.1449	-.1415	.0551	.0916	.0732
PLWEEC91	-.2981	-.1741	-.3020	.1180	.0812	.1339
STWTER91	-.2486	-.0485	-.2186	.1416	.0063**	.1317
STWTEG91	-.1573	-.1517	-.1712	.0613	.1062	.0787
STWTEC91	-.2720	-.0867	-.2503	.1450	.0303*	.1426
MWTR91	-.2529	-.0498	-.2224	.1439	.0068**	.1342
MWTG91	-.1650	-.1706	-.1838	.0618	.1049	.0796
MWTC91	-.2620	-.1062	-.2519	.1320	.0498	.1360

	MLOSER91	MLOSEG91	MLOSEC91	PADELR91	PADELG91	PADELC91
PLWEER91	.1492	.1110	.1804	.0275**	.1115	.0635
PLWEEG91	.0141**	.0503	.0528	.0281**	.0590	.0457
PLWEEC91	.1224	.1496	.1806	.0505	.0924	.0745
STWTER91	.1681	.0742	.1843	.0276**	.0852	.0476
STWTEG91	.0284**	.0630	.0632	.0383*	.0649	.0519
STWTEC91	.1598	.0921	.1880	.0435	.0913	.0616
MWTR91	.1709	.0726	.1860	.0223**	.0839	.0434
MWTG91	.0256**	.0619	.0661	.0411	.0646	.0544
MWTC91	.1527	.1173	.1972	.0476	.0661	.0568

NB All correlations are statistically significant at the 1% level unless indicated with a * (statistically significant at the 5% level) or a ** (not statistically significant at the 5% level).

Key:

PLWEER91	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1991-92
STWTEG91	Standardized waiting time, specialty G (gynaecology) 1991-92
MWTC91	Mean waiting time, specialties C (combined), 1991-92
PELDCR91	Proportion of elective episodes treated as day cases, specialty R (routine surgery) 1991-92
STLSEG91	Standardized length of stay, specialty G (gynaecology), 1991-92
MLOSEC91	Mean length of stay, specialties C (combined), 1991-92
PADELR91	Proportion of admissions that are elective episodes, specialty R (routine surgery), 1991-92

8.5.3 Utilization variables

It is also interesting to consider the relationship between waiting times and the utilization of inpatient services. Two measures of the utilization of inpatient services were constructed, one based on the number of episodes and the other on the costs of those episodes. Given the national average number of episodes by age, sex, and specialty, we calculated each ward's expected number of episodes given its demographic profile. For each ward, the episode-based utilization measure (UEPIS) was calculated as the actual number of episodes divided by the expected number of episodes. We were also supplied with a national average treatment and daily hotel cost for both surgery and gynaecology. Using these data, we attached an estimate of the actual cost to each episode. We also derived a national average cost for each episode in any age, sex, and specialty and, using this information, we attached an expected cost to each episode. Our cost-based measure of utilization (UCOS) was then the sum of the estimated costs divided by the sum of the expected costs, for all episodes in any given ward. As is well known, the HES data is unlikely to be error free and the statistical return KP70 was thought to provide more reliable annual totals for episodes. Consequently, for both of the utilization measures, each episode was multiplied by a factor defined as the ratio of the number of completed episodes from the KP70 return to that derived from the HES system for the DHA in which the episode took place.

The correlation coefficients between the various measures of waiting times and utilization are shown in Table 13 for 1991-92. (Similar results for 1990-91 data can be found in Table A8 in Appendix 2.) Generally, the relationship is a negative one, with utilization (perhaps reflecting demand) falling as waiting times increase. Again, this contrasts with the significant positive correlation between actual admissions and length of waiting list in 18 Districts in Trent RHA in 1975 (Frost and Francis, 1979).

Table 13 Correlation coefficients between the various measures of waiting time and the utilization of inpatient services, 1991-92

	UEPISR91	UEPISG91	UEPISC91	UCOSR91	UCOSG91	UCOSC91
PLWEER91	-.1765	-.1220	-.1840	-.1841	-.1014	-.1838
PLWEEG91	.0332*	-.0101**	.0225**	-.0740	-.0169**	-.0641
PLWEEC91	-.1124	-.1377	-.1408	-.1696	-.1053	-.1726
STWTER91	-.2033	-.0723	-.1844	-.2041	-.0785	-.1923
STWTEG91	.0287**	.0179**	.0308*	-.0791	.0016**	-.0613
STWTEC91	-.1683	-.0563	-.1508	-.2005	-.0624	-.1831
MWTR91	-.2048	-.0739	-.1863	-.2035	-.0804	-.1925
MWTG91	.0182**	.0028**	.0166**	-.0914	-.0131**	-.0765
MWTC91	-.1519	-.0947	-.1537	-.1958	-.0882	-.1882

NB All correlations are statistically significant at the 1% level unless indicated with a * (statistically significant at the 5% level) or a ** (not statistically significant at the 5% level).

Key:

PLWEER91	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1991-92
STWTEG91	Standardized waiting time, specialty G (gynaecology) 1991-92
MWTC91	Mean waiting time, specialties C (combined), 1991-92
UEPISR91	Standardized utilization rate (episodes), specialty R (routine surgery) 1991-92
UCOSG91	Standardized utilization rate (costs), specialty G (gynaecology) 1991-92

8.5.4 Socio-economic variables

Finally, Table 14 reports the correlation coefficients between two of the waiting times variables (for 1991-92) and several socio-economic and health indicators. (Similar results, using waiting time data for 1990-91, can be found in Table A9 in Appendix 2.) At first sight, some of the signs of these coefficients seem counter-intuitive. However, when it is remembered that all other factors are not being held constant then the coefficients seem less awry. For example, the relationship between waiting times and morbidity is negative although one might have expected wards with a higher rate of morbidity to be associated with longer waiting times (through the increased pressure on resources). However, such areas might attract more funding which, to an unknown extent, will offset the greater demand for health care.

Table 14 Correlation coefficients between two measures of waiting time and various socio-economic and health indicators, 1991-92

	PLWEER91	PLWEEG91	PLWEEC91	STWTER91	STWTEG91	STWTEC91
OWN_OCC	.2059	.2037	.2633	.1639	.1774	.1977
NO_CAR	-.1809	-.1632	-.2221	-.1835	-.1249	-.1975
OVER_CROWD	-.1338	-.1645	-.1900	-.1002	-.1400	-.1296
BLACK	-.2098	-.2256	-.2848	-.1516	-.2150	-.2039
OLD_ALONE	-.1864	-.1895	-.2335	-.1784	-.1599	-.2059
ONE_CARER	-.1128	-.0825	-.1375	-.1253	-.0447	-.1236
PERM_SICK	-.1415	-.0334*	-.1333	-.1927	-.0068**	-.1716
STUDENTS	-.R916	-.1586	-.2188	-.1592	-.1545	-.1921
UNEMPLOY	-.1394	-.1567	-.1895	-.1507	-.1213	-.1680
MANUAL	.1349	.1428	.1602	.0898	.1525	.1273
SIRI074	-.1338	-.0431	-.1387	-.1733	-.0106**	-.1556
SMR074	-.1536	-.0747	-.1622	-.1820	-.0557	-.1761
NEED	-.1575	-.0845	-.1742	-.1889	-.0524	-.1817

NB All correlations are statistically significant at the 1% level unless indicated with a * (statistically significant at the 5% level) or a ** (not statistically significant at the 5% level).

Key:

PLWEER91	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1991-92
STWTEG91	Standardized waiting time, specialty G (gynaecology) 1991-92
OWN_OCC	Proportion of persons living in owner-occupied accommodation
NO_CAR	Proportion in households with no car
OVER_CROWD	Proportion in households in crowded accommodation
BLACK	Proportion in Black ethnic groups
OLD_ALONE	Proportion of those of pensionable age living alone
ONE_CARER	Proportion of dependants in single carer households
PERM_SICK	Proportion of adult population permanently sick
STUDENTS	Proportion of working age population who are students
UNEMPLOY	Proportion of economically active that are unemployed
MANUAL	Proportion of persons in households with head in manual class
SIRI074	Standardized illness ratio for those aged under 75
SMR074	Standardized mortality ratio for those aged under 75
NEED	Weighted index of health needs based upon the OLD_ALONE, ONE_CARER, UNEMPLOY, SIRI074 and SMR074 variables. For an explanation of these weights, see Carr-Hill *et al.*, (1994).

Some of the correlation coefficients are clearly plausible. For example, access to a car is likely to improve the ability of a prospective patient to wait for treatment (by facilitating the person's ability to visit his or her GP). Hence the negative correlation coefficient. Similarly, one might expect the elderly living alone to be less able to wait for treatment. Hence the negative correlation coefficient between this variable and waiting times.

9. EMPIRICAL ESTIMATION

As explained in Part I, separate demand and supply equations were modelled. This Section describes in some detail the procedures that were followed in deriving the models reported in Part I.

The demand side was estimated by modelling utilization as a function of needs, waiting time, and the availability of substitute facilities, as outlined above. The needs variable was considered exogenous. However, because it is determined jointly by supply and demand equations, waiting time is considered an endogenous variable and thus two-stage least squares was used to estimate the demand equation. Indeed, a joint test of the endogeneity of waiting times, GP supply and the provision of private hospital beds, led us to reject the null hypothesis that these three variables were exogenous (($F_{3,4453}$)=91.5, $p < 0.001$).

Following the usual convention, the supply side was estimated by modelling waiting times as a function of supply and resources (i.e. by taking waiting time to the left hand side of the above supply equation). Both utilization and resources were considered endogenous, and hence two-stage least squares was again employed. Indeed, a joint test of the endogeneity of utilization, NHS beds, the proportion of elective episodes treated as day cases, the length of stay, and the proportion of all episodes that are electives, led us to reject the null hypothesis that these five variables were exogenous (($F_{5,4448}$)=35.4, $p < 0.001$). In addition, a further set of equations was estimated to model the response of supply and efficiency variables to waiting times, and these equations are discussed after the main model.

The unit of analysis was 4,985 small areas although about 500 wards had to be excluded due to data inadequacies. The utilization measure was based on the number of episodes. The length of stay, utilization and waiting times variables were all standardized i.e. they were adjusted to take account of the demographic profile of each ward. This removed the need to include age and sex variables in the demand and supply equations. Episodes in the gynaecology specialty were dropped and only routine surgery considered. This was done for two reasons: first, there are four times as many surgical episodes as there are gynaecological ones; and second, it was felt that the demand for and supply of gynaecological services might differ from that for routine surgery.

The endogenous variables in the model were instrumented using a sub-set of variables drawn from various health status variables as well as a large number of variables extracted from the 1991 Census of Population to reflect socio-economic conditions. In summary, these covered the following aspects of social and economic circumstances:

housing tenure
housing amenities
car ownership
overcrowding
ethic origin
elderly living alone
lone parents
students
migrants
unemployment
educational qualifications
social class
concealed families
non-earning households

Full details of the precise instrument set for each equation can be found in Appendix 3. Natural logarithms were taken of all variables and each observation (ward) was weighted in proportion to its number of elective episodes in 1991-92. Regional dummies were included in the supply equation but are not reported. For both the demand and supply equations we obtained good, convincing results. The estimated 2SLS demand equation, which shows no evidence of mis-specification, is reported in Table 15.

Table 15 The demand equation - the basic model

Dependent variable: utilization (number of episodes)

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	4	56.20737	14.051842
Residuals	4455	152.40549	.034210

F = 410.78557 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
WAIT_TIME91	-.089138	.018466	-.097622	-4.827	.0000
GP_SUPPLY	-.107345	.027113	-.123480	-3.959	.0001
PRIV_BEDS	-.091535	.011525	-.264679	-7.942	.0000
NEED	.799958	.028973	.532100	27.611	.0000
(Constant)	-1.538794	.053461		-28.784	.0000

Mis-specification test statistic = 0.62/(152.4/4456)= 18.1 $\chi^2_{.001}(12)$=32.6

Key:

WAIT_TIME91	Standardized waiting times for elective surgery, 1991-92
GP_SUPPLY	Supply of GPs
PRIV_BEDS	Provision of private hospital beds
NEED	Weighted index of health needs

The NEED variable is clearly significant and has a positive impact on demand. The waiting time variable is also significant and, as anticipated, has a negative effect. The supply of both GPs and private hospital beds also have the anticipated negative impact on the demand for NHS in-patient services.

Demand might respond to waiting times with a lag and, to examine this possibility, the above model was re-estimated with the waiting time for 1990-91 as a regressor. The resulting equation, shown in Table 16, is similar to that reported above except for the fact that the estimated coefficient on the waiting time variable is slightly reduced.

Table 16 The demand equation - with lagged waiting times as regressor

Dependent variable: utilization

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	4	56.25718	14.064294
Residuals	4455	153.99832	.034568

F = 406.89700 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
GP_SUPPLY	-.109492	.027306	-.125950	-4.010	.0001
PRIV_BEDS	-.091803	.011564	-.265455	-7.938	.0000
WAIT_TIME90	-.064003	.012930	-.068784	-4.950	.0000
NEED	.819997	.028944	.545429	28.330	.0000
(Constant)	-1.574186	.053401		-29.479	.0000

Mis-specification test statistic = 0.57/(154.0/4456)= 16.5 $\chi^2_{.001}(12)$=32.6

Key:

GP_SUPPLY	Supply of GPs
PRIV_BEDS	Provision of private hospital beds
WAIT_TIME90	Standardized waiting times for elective surgery, 1990-91
NEED	Weighted index of health needs

Table 17 reports the supply equation estimated using 2SLS. Like the demand result, this equation shows no evidence of misspecification. As anticipated, utilization has a positive impact on waiting times and increased supply of NHS beds significantly reduces waiting times. Another variable that has a significant (negative) impact on waiting times is the proportion of elective episodes that are treated as day cases. The length of stay variable, which includes day cases with a zero stay, has a positive but insignificant coefficient. The insignificance of this variable is not surprising given the level of correlation between it and the day case variable (ρ=-0.66). Moreover, when the latter variable is dropped from the model, the length of stay is now a significant determinant of waiting times (see Table 18). Re-estimation of the basic supply equation, dropping the insignificant length of stay variable, has very little effect on either the estimated coefficients or the model's specification (see Table 19).

Table 17 The supply equation - the basic model

Dependent variable: standardized waiting time

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	17	87.22271	5.1307477
Residuals	4442	140.47378	.0316240

F = 162.25529 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
UTILIZATION91	.355672	.033238	.324763	10.701	.0000
NHS_BEDS	-.256953	.013849	-.370522	-18.553	.0000
DAY_CASES	-.269184	.040026	-.261002	-6.725	.0000
LENGTH_STAY	.026908	.055536	.022471	.485	.6280
ELECTIVES	.114017	.039039	.078887	2.921	.0035
(Constant)	-.258089	.044442		-5.807	.0000

Mis-specification test statistic = 1.49/(140.5/4443)= 47.1 $\chi^2_{.001}$ (31)=61.0

Key:

UTILIZATION91	Standardized utilization rate (episodes), 1991-92
NHS_BEDS	Provision of NHS beds
DAY_CASES	Proportion of all elective episodes that are day cases
LENGTH_STAY	Standardized (for age and sex) length of stay
ELECTIVES	Proportion of all episodes that are electives

Table 18 The supply equation - omitting the day case variable

Dependent variable: standardized waiting time

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	85.79250	5.3620315
Residuals	4443	149.36509	.0336181

F = 159.51131 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
UTILIZATION91	.279294	.032207	.255023	8.672	.0000
NHS_BEDS	-.281985	.013754	-.406618	-20.502	.0000
LENGTH_STAY	.336207	.032097	.280769	10.475	.0000
ELECTIVES	.096774	.040164	.066956	2.409	.0160
(Constant)	.011428	.019808		.577	.5640

Mis-specification test statistic = 2.92/(149.4/4444)= 86.9 $\chi^2_{.001}$ (33)=63.6

UTILIZATION91	Standardized utilization rate (episodes), 1991-92
NHS_BEDS	Provision of NHS beds
LENGTH_STAY	Standardized (for age and sex) length of stay
ELECTIVES	Proportion of all episodes that are electives

Table 19 Re-estimating the basic supply equation without the length of stay variable

Dependent variable: waiting time

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	87.21529	5.4509555
Residuals	4443	140.30901	.0315798

F = 172.62286 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
UTILIZATION91	.357907	.032893	.326803	10.881	.0000
NHS_BEDS	-.256020	.013705	-.369178	-18.680	.0000
DAY_CASES	-.285244	.022421	-.276574	-12.722	.0000
ELECTIVES	.109343	.037802	.075653	2.893	.0038
(Constant)	-.276274	.023784		-11.616	.0000

Mis-specification test statistic = 1.50/(140.3/4444)= 47.5 $\chi^2_{.001}$ (32)=62.5

Key:

UTILIZATION91	Standardized utilization rate (episodes), 1991-92
NHS_BEDS	Provision of NHS beds
DAY_CASES	Proportion of all elective episodes that are day cases
ELECTIVES	Proportion of all episodes that are electives

10. SENSITIVITY ANALYSIS

Although we were guided by economic and econometric theory when developing the demand and supply models reported above, a number of judgements had to be made. It is, therefore, important to examine the robustness of the model with respect to different assumptions e.g. whether utilization should be measured in terms of the number or the cost of the episodes. Consequently, the model was re-estimated so that six issues relating to sensitivity analysis could be examined:

(a) variations across the country;
(b) using OLS rather than 2SLS to estimate the models;
(c) measuring utilization as the cost rather than the number of episodes;
(d) adding the gynaecology specialty;
(e) measuring waiting times as the proportion of patients waiting longer than 90 days;
(f) replacing the standardized variables with their mean counterpart.

These are now considered in turn.

The results from the re-estimation of the basic model across six different geographical areas are reported in Table 20. Qualitatively, the demand equation is similar in all six equations. The most marked changes, however, are associated with the results for the metropolitan areas and London. In these areas, the provision of private hospital beds no longer affects the demand for NHS facilities whilst the importance of waiting times increases.

Table 20 Sensitivity of the estimated model to geographical area - the demand equation

GEOGRAPHICAL AREA	GP_SUPPLY	PRIV_BEDS	NEED	WAIT_TIME	TEST STATISTIC
England	.11 (4.0)	-.09 (7.9)	.80 (27.6)	-.09 (4.8)	18.1
England minus inner London	-.09 (3.5)	-.06 (5.2)	.80 (27.6)	-.12 (6.5)	15.9
England minus all London	-.11 (4.1)	-.09 (5.6)	.83 (26.7)	-.08 (3.7)	12.4
Shire areas	-.08 (2.5)	-.08 (3.9)	.81 (16.8)	-.07 (2.9)	35.8
Metropolitan areas	-.31 (6.0)	.03 (1.7)	.67 (13.3)	-.20 (3.6)	103.1
All London	-.46 (1.6)	-.01 (0.1)	.72 (10.7)	-.19 (3.3)	99.5

Key:

GP_SUPPLY	GP supply
PRIV_BEDS	Provision of private hospital beds
WAIT_TIME	Standardized waiting times for elective surgery, 1991-92
NEED	Weighted index of health needs
TEST STATISTIC	Mis-specification test statistic; critical $\chi^2_{.001}(12)$=32.6

With the exception of the equation for the metropolitan areas, the various supply equations in Table 21 are remarkably similar and show no evidence of mis-specification. As was the case with the demand equation, some of the coefficients in the London equation are markedly different to those for the country as a whole. For example, the provision of NHS beds has a much stronger impact on waiting times in London than elsewhere. The result for the metropolitan areas is interesting because it reveals a strong positive impact of length of stay on waiting times - a result which although expected has not been found for other areas. However, the coefficient on the day cases variable is positive which is rather counter-intuitive.

Table 21 Sensitivity of the estimated model to geographical area - the supply equation

Geographical area	UTILI-SATION	NHS_BEDS	DAY_CASES	LENGTH_OF STAY	ELECTIVES	Test statistic
England	.35 (10.7)	-.26 (18.5)	-.27 (6.7)	.03 (0.5)	.11 (2.9)	47.1
England minus inner London	.35 (10.7)	-.22 (15.8)	-.24 (6.1)	.06 (1.0)	.06 (1.6)	39.9
England minus all London	.34 (9.7)	-.22 (14.1)	-.25 (5.9)	.02 (0.4)	.08 (2.1)	33.3
Shire areas	.35 (8.1)	-.13 (6.0)	-.47 (8.5)	-.22 (2.8)	.19 (3.5)	37.3
Metropolitan areas	.27 (5.0)	-.69 (10.9)	.36 (4.3)	.65 (6.0)	-.36 (5.2)	87.4
All London	.33 (4.0)	-.82 (8.1)	-.42 (3.1)	.13 (0.7)	.03 (0.2)	47.4

Key:

UTILIZATION91	Standardized utilization rate (episodes), 1991-92
NHS_BEDS	Provision of NHS beds
DAY_CASES	Proportion of all elective episodes that are day cases
LENGTH_STAY	Standardized (for age and sex) length of stay
ELECTIVES	Proportion of all episodes that are electives
TEST STATISTIC	Mis-specification test statistic; critical $\chi^2_{.001}$ (33)=63.6

Having examined the sensitivity of the model to different geographical areas, Table 22 reports five further equations in which the basic demand model has been modified and then re-estimated using the same data set. The OLS result is similar to that using 2SLS but the provision of private hospital beds appears to be insignificant. Using episode costs to measure utilization (rather than the number of episodes) yields a qualitatively similar result but GP supply is no longer statistically significant. The addition of gynaecological episodes to the data set has a similar impact, with GP supply no longer significant, although the significance of waiting times as a demand deterrent is much reduced.

The impact of using the proportion of those waiting longer than 30 days rather than the standardized waiting time is, again, quantitative rather than qualitative. GP supply and the availability of private hospital beds are only of marginal significance, while the impact and significance of waiting times increases. Even the replacement of the standardized variables with the straight forward mean has no qualitative impact although both the waiting time and GP supply are no longer significant. The evidence of substantial misspecification is to be anticipated as no allowance has been made in this particular equation for the impact of the ward's demographic profile on its utilization rate (number of episodes per head).

Table 22 Sensitivity of estimated model to various adjustments - the demand equation

ADJUSTMENT	GP_SUPPLY	PRIV_BEDS	NEED	WAIT_TIME	TEST STATISTIC
None - basic model	.11 (4.0)	-.09 (7.9)	.80 (27.6)	-.09 (4.8)	18.1
OLS rather than 2SLS	-.08 (6.5)	.00 (0.3)	.78 (35.0)	-.11 (9.6)	n/a
Utilization measured as cost rather than episodes	-.04 (1.6)	-.03 (2.9)	.82 (28.9)	-.13 (7.3)	89.3
Addition of gynaecology to surgery	-.04 (1.5)	-.11 (9.2)	.86 (27.9)	-.04 (1.9)	51.4
Proportion waiting > 90 days rather than standardized wait	-.05 (1.9)	-.12 (1.7)	.84 (27.0)	-.13 (9.5)	68.7
Replace standardized variables with mean of unadjusted	-.04 (0.9)	-.28 (14.9)	.46 (9.9)	-.01 (0.4)	278.2

Key:

GP_SUPPLY	GP supply
PRIV_BEDS	Provision of private hospital beds
WAIT_TIME	Standardized waiting times for elective surgery, 1991-92
NEED	Weighted index of health needs
TEST STATISTIC	Mis-specification test statistic; critical $\chi^2_{.001}(12)$=32.6

The results of applying the same sensitivity analysis to the supply equation (see Table 23) are broadly similar to those obtained on the demand side. Throughout, the estimated coefficients on the utilization, NHS beds and proportion of day cases variables are very similar. The OLS model gives the 'wrong' sign to the length of stay and electives variables, and in the other equations even the signs on these variables yield no consistent pattern. This probably reflects the relatively weak effect that these variables have on waiting times.

Table 23 Sensitivity of estimated model to various adjustments - the supply equation

Adjustment	UTILI-SATION	NHS_BEDS	DAY_CASES	LENGTH_OF STAY	ELECTIVES	Test statistic
None - basic model	.35 (10.7)	-.25 (18.5)	-.26 (6.7)	.02 (0.4)	.11 (2.9)	47.1
OLS rather than 2SLS	.13 (8.1)	-.22 (23.8)	-.29 (15.9)	-.04 (2.0)	-.05 (2.6)	n/a
Utilisaion measured as cost rather than episode	.36 (10.3)	-.27 (19.2)	-.32 (7.5)	-.16 (2.6)	.13 (3.2)	52.1
Addition of gynaecology to surgery	.32 (11.6)	-.31 (24.0)	-.38 (3.8)	.13 (2.3)	-.00 (0.0)	88.1
Proportion waiting > 90 days rather than standardized wait	.35 (9.8)	-.24 (16.9)	-.82 (7.1)	-.02 (0.4)	.20 (2.8)	135.7
Replacing standardized variables with mean of unadjusted	.27 (8.9)	-.24 (17.9)	-.38 (10.8)	-.24 (5.8)	-.22 (4.5)	70.0

Key:

UTILIZATION91	Standardized utilization rate (episodes), 1991-92
NHS_BEDS	Provision of NHS beds
DAY_CASES	Proportion of all elective episodes that are day cases
LENGTH_STAY	Standardized (for age and sex) length of stay
ELECTIVES	Proportion of all episodes that are electives
TEST STATISTIC	Mis-specification test statistic; critical $\chi^2_{.001}$ (33)=63.6

11. MODELLING NHS PROCESS VARIABLES

It was mentioned above that the supply and efficiency variables might themselves be influenced by, amongst other things, waiting times. If this is the case, then to ascertain the impact on waiting times of, say, an increase in NHS beds, then estimates of these relationships are required. We considered it impractical and fruitless to model the multitude of factors that influence the provision of NHS acute beds, the provision of private acute beds, and GP supply. Instead we concentrate on process variables, treating each in turn.

11.1 The proportion of elective episodes that are treated as day cases

Long waiting times will increase the pressure to treat more patients as day cases. The availability of after care, whether provided by the NHS (via outpatients or GPs) or by less formal arrangements, will also facilitate the use of day case treatments. More wealthy areas might have better after care possibilities as well as generating less severe cases, and both factors are likely to facilitate the use of day cases. Finally, the impact of the provision of private hospital beds is unpredictable. It might be that by treating the more routine cases, a smaller proportion of the remaining cases can be treated as day cases. Alternatively, it might be that it is the more dynamic and innovative surgeons that are involved with the private sector and it is these very individuals who are also the most likely to use day case treatments. Thus our hypothesized model is of the form:

Proportion of
elective episodes
treated as day cases = f(waiting time (+),
provision of NHS beds (+),
GP supply (+),
availability of informal after care (+),
need (-)),
provision of private hospital beds (?)).

The equation we derived broadly supported our hypotheses (see Table 24). Waiting times have a positive (albeit statistically insignificant) effect on the dependent variable while high need areas tend to have a lower proportion of day cases. Both GP supply and the provision of NHS beds have a statistically insignificant impact on the use of day cases. Quite sensibly, the proportion of dependants living without a carer has a negative impact on the use of day cases, as does the proportion of residents living in households without central heating. The latter variable can be interpreted as an indicator of need. With the exception of the sign on the manual variable, this model is sensible and shows no evidence of misspecification. It suggests that in 1991-92 socio-economic factors and, in particular, the availability of informal after care, were the main determinants of the use of day cases and that waiting times played a very minor role.

Table 24 Modelling the proportion of episodes that are day cases

Dependent variable: the proportion of episodes that are day cases

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	20	53.21969	2.6609844
Residuals	4439	171.88717	.0387220

F = 68.72566 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
WAIT_TIME91	.071594	.090397	.073838	.792	.4284
NEED	-.275255	.047542	-.172418	-5.790	.0000
PRIV_BEDS	.169852	.046628	.462515	3.643	.0003
GP_SUPPLY	.002103	.034263	.002278	.061	.9511
NHS_BEDS	.035569	.060594	.052898	.587	.5572
NO_C_HEATING	-.034845	.006054	-.118722	-5.756	.0000
MANUAL	.108946	.015407	.176667	7.071	.0000
NO_CARER	-.099541	.012020	-.152454	-8.282	.0000
(Constant)	-.037535	.211624		-.177	.8592

Mis-specification test statistic = 2.46/(171/4440)= 63.9 $\chi^2_{.001}$ (35)=66.4

WAIT_TIME91	Standardized waiting times for elective surgery, 1991-92
NEED	Weighted index of health needs
PRIV_BEDS	Provision of private hospital beds
GP_SUPPLY	GP supply
NHS_BEDS	Provision of NHS beds
NO_C_HEATING	Proportion of residents in households with no central heating
MANUAL	Proportion of persons in households with head in manual class
NO_CARER	Proportion of dependants in "no carer" households

11.2 The standardized length of stay

It is to be anticipated that long waiting times will reduce the length of stay as attempts are made to treat more cases. Clearly, the greater is the use of day cases, the shorter will be the length of stay. High GP availability will make after care easier and thus facilitate earlier discharge from hospital. NHS (outpatient) provision could also have the same effect. Private hospitals, by treating the less severe cases, may increase the average length of stay of those who are treated in the NHS. Again, the availability of informal social support will influence the length of stay and these effects should be captured by the socio-economic variables available to us. Those patients from more deprived backgrounds might have more severe conditions and/or take longer to recover; variables reflecting social deprivation should indicate this effect. Thus our hypothesized model is of the form:

Length of stay = f(waiting time (-),
proportion of electives that are day cases (-),
provision of NHS beds (-),
GP supply (-),
availability of informal after care (-),
deprivation indicators (+),
provision of private hospital beds (+)).

The equation reported in Table 25 broadly supports our hypotheses although it is noticeable that the waiting time variable does not have the anticipated negative sign (it is insignificantly different from zero). GP supply and the proportion of episodes that are day cases both have a strong negative impact on the length of stay. The negative sign on the NO_CARER variable might reflect the fact that areas with high levels of dependents living without a carer have a relatively well developed nursing and residential home sector which can accommodate discharges earlier than informal carers. The variables measuring the proportion of residents in private rented accommodation and the proportion of residents in households with no car are both indicators of deprivation, and both have the anticipated positive impact on the length of stay.

Table 25 Modelling the standardized length of stay in hospital

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	22	60.380432	2.7445651
Residuals	4439	80.459867	.0181257

F = 151.41208 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
WAIT_TIME91	.031905	.026970	.038204	1.183	.2369
DAY_CASES	-.619839	.016098	-.719668	-38.503	.0000
PRIV_BEDS	.044822	.031846	.141711	1.407	.1594
GP_SUPPLY	-.189949	.028638	-.238906	-6.633	.0000
NHS_BEDS	.047003	.044605	.081160	1.054	.2921
PRIV_RENTED	.016989	.003581	.069341	4.745	.0000
NO_CAR	.103893	.011837	.327445	8.777	.0000
OVERCROWDING	-.028545	.006360	-.107202	-4.489	.0000
BLACK*	-.275575	.067381	-.064121	-4.090	.0000
NO_CARER	-.063685	.010749	-.113246	-5.925	.0000
(Constant)	-.617248	.125281		-4.927	.0000

Mis-specification test statistic = 0.7 $\chi^2_{.001}$ (35)=66.4

WAIT_TIME91	Standardized waiting times for elective surgery, 1991-92
DAY_CASES	Proportion of all elective episodes that are day cases
PRIV_BEDS	Provision of private hospital beds
GP_SUPPLY	GP supply
NHS_BEDS	Provision of NHS beds
PRIV_RENTED	Proportion of residents in private rented accommodation
NO_CAR	Proportion of residents in households with no car
OVERCROWDING	Proportion of residents in crowded accommodation
BLACK*	1-proportion of residents in black ethnic groups
NO_CARER	Proportion of dependents in no carer households

The insignificance of the waiting times variable in both the day case and length of stay models is, at first, slightly surprising given the apparent endogeneity of these variables in the basic supply equation. Rather than detecting endogeneity, however, that test result might indicate that these variables reflect some element of case mix which we have been unable explicity to include in the supply equation.

11.3 The proportion of all episodes that are elective

The impact of waiting times on the proportion of all episodes that are elective admissions is unpredictable. As waiting times increase, more patients might be admitted as emergencies yielding a negative relationship. Alternatively, as waiting times increase more resources might be devoted to their reduction thus generating a positive relationship. It is also to be expected that as the provision of NHS beds increases so too will the proportion of all episodes that are elective, and the efficiency with which the available beds are used will also have a positive impact. To the extent that GPs undertake minor surgery and private hospitals offer substitutes for NHS treatment then the availability of both of these facilities is likely to reduce the proportion of all episodes that are elective. In high need areas, patients are likely to be less able to wait for treatment than their counterparts in lower need areas. Hence high need areas are likely to have a lower proportion of admissions that are elective episodes. Thus our model is:

The proportion of all episodes that are elective	=	f(	waiting times (?), the provision of NHS beds (+), the proportion of episodes that are day cases (+), the length of stay in hospital (-), GP supply (-), the provision of private hospital beds (-), index of need (-)).

The equation we obtained, which shows no evidence of misspecification,
is reported in Table 26 and is broadly consistent with our hypotheses. The only additional variable which is significant and which we had not anticipated is the proportion of residents aged 75+ in residential/nursing homes. This variable has a negative impact on the proportion of elective admissions. One explanation might be that individuals in such accommodation are relatively high dependency.

Table 26 Modelling the proportion of all admissions that are electives

Dependent variable: the proportion of all episodes that are elective

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	20	44.832650	2.2416325
Residuals	4441	94.022066	.0211714

F = 105.87577 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
WAIT_TIME91	.290907	.059514	.420456	4.888	.0000
NHS_BEDS	.210621	.040568	.438964	5.192	.0000
DAY_CASES	.148023	.033845	.207439	4.374	.0000
LENGTH_STAY	-.239845	.046249	-.289495	-5.186	.0000
GP_SUPPLY	-.056118	.023356	-.085192	-2.403	.0163
PRIV_BEDS	-.232496	.031174	-.887224	-7.458	.0000
NEED	-.195807	.026580	-.171885	-7.367	.0000
HOMES*	.119987	.032819	.054960	3.656	.0003
(Constant)	-.859743	.146893		-5.853	.0000

Mis-specification test statistic = 1.22/(94/4442)=57.7 $\chi^2_{.001}$ (30)=59.7

Key:

WAIT_TIME91	Standardized waiting times for elective surgery, 1991-92
NHS_BEDS	Provision of NHS beds
DAY_CASES	Proportion of all elective episodes that are day cases
LENGTH_STAY	Standardized (for age and sex) length of stay
GP_SUPPLY	GP Supply
PRIV_BEDS	Provision of private hospital beds
NEED	Weighted index of health needs
HOMES*	1-proportion of residents aged 75+ in residential/nursing homes

Taken together, the results in this section considerably simplify the analysis of waiting times. Our models of the use of day cases and the length of stay suggest that waiting times have no significant impact upon these variables. The material presented in this section suggests that an adequate analysis of waiting times can be achieved by focusing on the basic supply and demand equations reported above as well as the model explaining the proportion of all admissions that are electives.

APPENDIX 1: MEASURING SUPPLY

A fundamental need in this study was to develop a measure of the *perceived availability* of various health care services to a particular small area. This measure should incorporate three elements: the inherent attractiveness of services; their proximity to the population of interest; and the effect of competing populations. The traditional method of treating such concepts is to develop a measure of the *accessibility* of the ward to health care services. This is achieved here using the ideas of spatial interaction modelling described by Wilson (1974).

The standard spatial interaction model is of the form:

$$T_{id}=gP_iS_d\,f(c_{id}) \qquad \textbf{(1)}$$

where T_{id} is the number of interactions (say, hospital episodes per year) between residential zone i and destination d;

P_i is some measure of the effective population of zone i;

S_d is some measure of the size or attractiveness of destination d;

c_{id} is some measure of distance (or time) between i and d;

f(.) is a distance decay or deterrence function;

g is a gravitational constant.

Then the total number of interactions (say, hospital episodes) T_i generated by zone i per year is given by

$$T_i=gP_i\sum_d S_d\,f(c_{id}) \qquad \textbf{(2)}$$

and the number of episodes T_d attracted to destination (hospital) d is

$$T_d=gS_d\sum_i P_i\,f(c_{id}) \qquad \textbf{(3)}$$

Now in this study each hospital (destination) is limited in the number of patients it can treat. That is, the model is "attraction constrained" (Batty, 1976, p39). It is therefore necessary to introduce a balancing factor B_d into the model for each destination d, so that (1) is rewritten

$$T_{id}=gP_iB_dS_d\, f(c_{id}) \tag{4}$$

where

$$B_d=\frac{1}{\sum_i P_i\, f(c_{id})} \tag{5}$$

Introduction of the factor B_d ensures that the influence of competing populations is properly modelled.

Then the accessibility A_i of zone i to hospital facilities can be given by the ratio of predicted number of episodes in relation to population, which is represented by the expression

$$A_i=\left(\sum_d T_{id}\right)/P_i=\sum_d B_dS_d\, f(c_{id})=\sum_d\left(\frac{S_d\, f(c_{id})}{\sum_r P_r\, f(c_{rd})}\right) \tag{6}$$

Expression (6) models the *relative* accessibility of residents in zone j to all hospital resources, given the availability of beds (S_d), the distance to the hospitals (c_{id}) and the competition from local populations. It is a *distance weighted* form of the simple ratio "beds per head".

Thus in order to calculate the accessibility of residential zones, it is first necessary for each hospital to calculate the index B_d . Once the form of the deterrence function has been chosen, this is straightforward. Choice of measures for P_i and S_d is also straightforward: population and beds serve as reasonable proxies for demand (people) and supply (episodes). (Note that *demographic* determinants of utilization were treated elsewhere in this study, so that the population did not have to be weighted by need. The measure A_i is merely intended to give a measure of relative inpatient provision.) The measure of distance c_{id} should ideally be a measure of *perceived* distance, or possibly journey time. However, in this study the only available distance measures were straight line (or crow fly) distances, so these had to be used. A standard intrazonal cost was added to each distance.

Finally, possibly the most troublesome aspect of modelling is the choice of deterrence function f(.). Scrutiny of the spatial location literature suggests a wide range of possible functional forms. Haggett, Cliff and Frey (1977) describe two in widespread use:

$$f(c)=e^{-\beta c^{\alpha}}$$
$$f(c)=c^{-\beta} \tag{7}$$

where c is distance and α and β are parameters to be estimated.

The distance function can be calibrated using a gravity model of the sort described by Batty (1976), in which case the parameters α and β are chosen to maximize a suitable likelihood function. Because we had no information about hospital of treatment we could not calibrate a gravity model. The original Newtonian model of physical gravitation uses the second of the functional forms with $\beta = 2$ (the inverse square law). Unfortunately, in modelling social phenomena, there is no guarantee that such a neat result exists. As a result, it was necessary to appeal to previous studies and judgement to model deterrence.

Batty uses both functional forms for subregional modelling. Using the first, he sets $\alpha = 1$, and estimates β by an iterative process such that modelled mean trip length equals observed mean trip length. Values of between 0.1 and 0.3 are found. Using the second, values of β between 1.5 and 2.5 are found. In another study, Foot (1981) uses the first functional form with $\alpha = 1$ and $\beta = 0.2$. The relevance of these values to the current study is limited because of the very particular type of spatial interaction being modelled. Indeed, we might expect that - for different types of NHS referral - different types of deterrence might occur. The only directly relevant work is the study of London hospitals reported by Mayhew (1986). However, he gives no values for the deterrence function parameters. In general, relatively minor conditions might be expected to exhibit high elasticity with respect to distance (high values of β) while lower values of β might obtain for, say, regional specialties. Bearing in mind that we wished to arrive at a relatively broad brush measure of accessibility, it was unnecessary to model such subtleties.

Instead, accessibility was modelled using the following two deterrence functions:

$$\begin{aligned} f(d) &= e^{-0.2c} \\ f(d) &= c^{-2} \end{aligned} \qquad \textbf{(8)}$$

The measures of accessibility implicit in these choices were examined to check that they were reasonable. It was eventually decided to use an inverse square deterrence function with intrazonal cost of 10 kilometres.

Although the discussion in this Appendix refers to NHS hospital accessability, exactly the same methods were used to model the provision of GP services and of private inpatient facilities. The only differences were in the measures S_d of the size or attractiveness of destination d. For GPs, the destination became a GP surgery, and the size was the number of registered GPs. For private hospitals, the destination was the local authority ward, and the size was the number of visitors (presumed to be inpatients) in non-psychiatric hospitals on Census night.

Clearly, these supply variables are necessarily crude. However, given the complexity of the concept of NHS supply, we believe they offer the best available proxies for the availability of health care to small areas.

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APPENDIX 2: RESULTS FOR 1990-91

Table A1 Finished consultant episodes for routine surgery and gynaecology, 1990-91, by RHA of treatment

RHA of treatment	Number of episodes	Number of electives	%	Number of electives with wait	%
Northern	271,718	181,419	66.8	160,437	88.4
Yorkshire	360,643	209,909	58.2	180,042	85.8
Trent	348,340	226,043	64.9	222,522	98.4
East Anglia	158,754	102,387	64.5	94,631	92.4
NW Thames	217,211	136,303	62.8	114,808	84.2
NE Thames	405,335	266,888	65.8	252,990	94.8
SE Thames	277,548	185,500	66.8	137,740	74.3
SW Thames	196,773	130,087	66.1	121,017	93.0
Wessex	210,259	146,550	69.7	103,406	70.6
Oxford	167,759	102,612	61.2	96,553	94.1
South West	240,603	162,086	67.4	161,398	99.6
West Midlands	382,368	252,641	66.1	198,270	78.5
Mersey	212,228	144,510	68.1	137,448	95.1
North West	379,079	265,477	70.0	244,450	92.1
SHAs	33,547	26,346	78.5	24,787	94.1
England	3,862,165	2,538,758	65.7	2,538,758	88.6

Table A2 Waiting time by RHA of treatment for routine surgery and gynaecology, 1990-91: number and percentage of episodes by length of wait

Count / Row Pct / RHA	Waiting time (days) 1-30	31-90	91-180	181-365	366-730	731-1095	Row Total
Northern	67741 44.2	42780 27.9	22135 14.4	15026 9.8	4836 3.2	838 .5	153356 7.2
Yorkshire	43556 37.2	32997 28.2	19546 16.7	13435 11.5	6675 5.7	841 .7	117050 5.5
Trent	85969 41.7	57689 28.0	30231 14.7	21471 10.4	9421 4.6	1469 .7	206250 9.7
East Angli	36469 38.7	25418 27.0	15743 16.7	10742 11.4	4832 5.1	945 1.0	94149 4.4
NW Thames	51146 44.7	33037 28.9	15759 13.8	9862 8.6	3836 3.4	743 .6	114383 5.4
NE Thames	99685 39.8	72902 29.1	35566 14.2	27000 10.8	12251 4.9	3326 1.3	250730 11.8
SE Thames	51622 37.7	39496 28.9	21826 15.9	15546 11.4	6917 5.1	1474 1.1	136881 6.4
SW Thames	46106 38.2	35909 29.8	19026 15.8	12142 10.1	6085 5.0	1367 1.1	120635 5.7
Wessex	34465 33.5	30851 30.0	17419 16.9	13815 13.4	5351 5.2	1053 1.0	102954 4.8
Oxford	35048 36.5	29125 30.3	14318 14.9	10699 11.1	5629 5.9	1146 1.2	95965 4.5
South West	59814 37.2	42091 26.2	26151 16.3	20927 13.0	10040 6.3	1602 1.0	160625 7.5
WestMidlan	69134 35.1	58587 29.7	32063 16.3	23595 12.0	11718 5.9	1956 1.0	197053 9.2
Mersey	54641 39.8	41935 30.5	21621 15.7	14324 10.4	4412 3.2	405 .3	137338 6.4
North West	88863 36.5	77340 31.7	34870 14.3	27199 11.2	12953 5.3	2383 1.0	243608 11.4
Column Total	824259 38.7	620157 29.1	326274 15.3	235783 11.1	104956 4.9	19548 .9	2130977 100.0

Table A3 Average waiting time and number of episodes by age and sex for routine surgery and gynaecology, 1990-91

Mean Count Age	Males	Females	Row Total
under 1	43.41	43.93	43.60
1-4	97.83	91.82	95.77
5-9	124.18	128.33	125.87
10-14	106.11	115.03	110.50
15-19	109.06	91.02	97.75
20-24	115.87	85.62	95.92
25-29	115.22	88.98	97.63
30-34	114.27	93.07	100.18
35-39	112.27	92.80	99.23
40-44	108.10	90.18	95.82
45-49	105.87	85.56	92.10
50-54	103.08	84.29	91.40
55-59	104.47	92.17	97.81
60-64	106.62	93.82	100.35
65-69	105.39	100.98	103.31
70-74	106.16	107.54	106.81
75-79	105.12	115.86	110.49
80-84	104.94	121.96	114.21
over 85	103.69	125.78	117.41
Column Total	108.14	96.05	101.18

Table A4 Mean waiting time by RHA of residence for routine surgery and gynaecology, 1990-91

RHA of residence	Average wait (days)	Rank	Number of episodes	Net inflow of episodes
Northern	84.1	1	152,512	-844
Yorkshire	105.6	7	121,174	4,124
Trent	95.6	5	218,041	11,791
East Anglia	105.6	13	85,502	-8,647
NW Thames	84.6	4	134,090	19,707
NE Thames	103.0	8	227,071	-23,659
SE Thames	105.9	9	133,651	-3,230
SW Thames	101.2	6	127,890	7,255
Wessex	110.5	11	104,481	1,527
Oxford	108.9	10	95,125	-840
South West	113.1	14	160,679	54
West Midlands	109.8	12	195,543	-1,510
Mersey	87.7	2	140,223	2,885
North West	104.0	3	234,995	-8,613
England	101.2		2,130,977	n/a

NB If rank=1, RHA has shortest wait, if rank=14, RHA has longest wait.

Table A5 Correlation coefficients between the three measures of waiting times for the three specialty groupings, 1990-91

	PLWEER90	PLWEEG90	PLWEEC90	STWTER90	STWTEG90	STWTEC90
PLWEER90	1.0000	.2948	.9295	.8625	.2904	.8490
PLWEEG90	.2948	1.0000	.5704	.2454	.8679	.4512
PLWEEC90	.9295	.5704	1.0000	.7971	.5310	.8695
STWTER90	.8625	.2454	.7971	1.0000	.2523	.9622
STWTEG90	.2904	.8679	.5310	.2523	1.0000	.4837
STWTEC90	.8490	.4512	.8695	.9622	.4837	1.0000
MWTR90	.8641	.2428	.7962	.9991	.2503	.9603
MWTG90	.2877	.8661	.5281	.2491	.9940	.4779
MWTC90	.8414	.4510	.8785	.9513	.4847	.9918

	MWTR90	MWTG90	MWTC90
PLWEER90	.8641	.2877	.8414
PLWEEG90	.2428	.8661	.4510
PLWEEC90	.7962	.5281	.8785
STWTER90	.9991	.2491	.9513
STWTEG90	.2503	.9940	.4847
STWTEC90	.9603	.4779	.9918
MWTR90	1.0000	.2467	.9501
MWTG90	.2467	1.0000	.4831
MWTC90	.9501	.4831	1.0000

NB All correlations are statistically significant at the 1% level

Key:

PLWEER90	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1990-91
STWTEG90	Standardised waiting time, specialty G (gynaecology) 1990-91
MWTC90	Mean waiting time, specialties combined, 1990-91

Table A6 Correlation coefficients between the various measures of waiting times and the supply of health care, 1990-91

	NHS_BEDS	GP_SUPPLY	HOMES	PRIV_BEDS
PLWEER90	-.3972	-.1508	.0580	-.1148
PLWEEG90	-.2860	-.1747	.1034	-.1373
PLWEEC90	-.4586	-.2102	.0961	-.1819
STWTER90	-.3573	-.1451	.0397	-.0460
STWTEG90	-.2409	-.1369	.0951	-.1033
STWTEC90	-.3935	-.1747	.0625	-.0835
MWTR90	-.3519	-.1349	.0415	-.0384
MWTG90	-.2462	-.1541	.0925	-.1065
MWTC90	-.4075	-.1858	.0750	-.0982

NB All correlations are statistically significant at the 1% level.

Key:

PLWEER90	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1990-91
STWTEG90	Standardised waiting time, specialty G (gynaecology), 1990-91
MWTC90	Mean waiting time, specialties C (R and G combined), 1990-91
NHS_BEDS	Supply of NHS beds
GP_SUPPLY	GP supply
HOMES	Proportion of residents aged 75+ living in residential/nursing homes
PRIV_BEDS	Supply of private hospital beds

Table A7 Correlation coefficients between the various measures of waiting times and the efficiency and process of inpatient services, 1990-91

	PELDCR90	PELDCG90	PELDC90	MLOSR90	MLOSG90	MLOSC90
PLWEER90	-.2342	-.1012	-.2436	.0156**	.0688	.0571
PLWEEG90	.0230**	-.1315	-.0314*	-.1430	-.0164**	-.1089
PLWEEC90	-.1548	-.1532	-.2022	-.0528	.0864	.0204**
STWTER90	-.2594	-.1038	-.2708	.0124**	.0304*	.0386
STWTEG90	.0296*	-.1407	-.0331*	-.1421	.0069**	-.1059
STWTEC90	-.2223	-.1296	-.2512	-.0350*	.0364*	.0035**
MWTR90	-.2631	-.1002	-.2724	.0145**	.0290**	.0394
MWTG90	.0371*	-.1496	-.0318*	-.1494	.0038**	-.1092
MWTC90	-.1941	-.1586	-.2439	-.0447	.0544	.0151**

	MLOSER90	MLOSEG90	MLOSEC90	PADELR90	PADELG90	PADELC90
PLWEER90	.0943	.1094	.1398	.0003**	.0014**	-.0057**
PLWEEG90	-.0438	.0762	.0047**	.0673	.0457	.0593
PLWEEC90	.0571	.1455	.1285	.0313*	-.0269**	.0069**
STWTER90	.1261	.0702	.1597	-.0081**	.0063**	-.0120**
STWTEG90	-.0397	.0954	.0132**	.0448	.0196**	.0304*
STWTEC90	.1021	.0878	.1485	.0062**	.0038**	-.0039**
MWTR90	.1248	.0685	.1576	-.0114**	.0044**	-.0153**
MWTG90	-.0465	.0995	.0127**	.0427	.0141**	.0262**
MWTC90	.0912	.1116	.1544	.0084**	-.0342*	-.0156**

NB All correlations are statistically significant at the 1% level unless indicated with a * (statistically significant at the 5% level) or a ** (not statistically significant at the 5% level).

Key:

PLWEER90	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1990-91
STWTEG90	Standardised waiting time, specialty G (gynaecology) 1990-91
MWTC90	Mean waiting time, specialties C (combined), 1990-91
PELDCR90	Proportion of elective episodes treated as day cases, specialty R (routine surgery) 1990-91
STLSEG90	Standardised length of stay, specialty G (gynaecology), 1990-91
MLOSEC90	Mean length of stay, specialties combined, 1990-91
PADELR90	Proportion of admissions that are elective episodes, specialty R (routine surgery), 1990-91

Table A8 Correlation coefficients between the various measures of waiting time and the utilisation of inpatient services, 1990-91

	UEPISR90	UEPISG90	UEPIC90	UCOSR90	UCOSG90	UCOSC90
PLWEER90	-.1563	-.0402	-.1394	-.1500	.0201**	-.1238
PLWEEG90	.0380*	.0376*	.0438	-.0647	.0251**	-.0486
PLWEEC90	-.0957	-.0776	-.1054	-.1431	-.0125**	-.1271
STWTER90	-.1446	-.0247**	-.1240	-.1442	.0098**	-.1217
STWTEG90	.0517	.0594	.0637	-.0525	.0544	-.0290**
STWTEC90	-.1102	-.0086**	-.0907	-.1425	.0228**	-.1162
MWTR90	-.1453	-.0223**	-.1237	-.1434	.0118**	-.1204
MWTG90	.0429	.0456	.0515	-.0639	.0434	-.0422
MWTC90	-.0972	-.0672	-.1020	-.1421	-.0178**	-.1274

NB All correlations are statistically significant at the 1% level unless indicated with a * (statistically significant at the 5% level) or a ** (not statistically significant at the 5% level).

Key:

PLWEER90	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1990-91
STWTEG90	Standardised waiting time, specialty G (gynaecology) 1990-91
MWTC90	Mean waiting time, specialties combined, 1990-91
UEPISR90	Standardised utilisation rate (episodes), specialty R (routine surgery) 1990-91
UCOSG90	Standardised utilisation rate (costs), specialty G (gynaecology) 1990-91

Table A9 Correlation coefficients between two measures of waiting time (1990-91) and various socio-economic and health indicators

	PLWEER90	PLWEEG90	PLWEEC90	STWTER90	STWTEG90	STWTEC90
OWN_OCC	.2239	.1990	.2856	.1792	.1697	.2134
NO_CAR	-.1662	-.1477	-.2162	-.1516	-.1028	-.1695
OVERCROWD	-.1306	-.1593	-.1986	-.1052	-.1313	-.1368
BLACK	-.2415	-.2359	-.3319	-.1980	-.2181	-.2513
OLD_ALONE	-.1778	-.1565	-.2256	-.1646	-.1188	-.1878
ONE_CARER	-.1245	-.0651	-.1500	-.1047	-.0334*	-.1077
PERM_SICK	-.1015	-.0031**	-.0907	-.0984	.0328*	-.0779
STUDENTS	-.2169	-.1525	-.2399	-.2097	-.1505	-.2346
UNEMPLOY	-.1494	-.1451	-.2058	-.1371	-.1049	-.1578
MANUAL	.1623	.1309	.1785	.1501	.1492	.1786
SIRI074	-.1002	-.0180**	-.1082	-.0968	.0188**	-.0831
SMR074	-.1202	-.0655	-.1346	-.1077	-.0272**	-.1031
NEED	-.1327	-.0638	-.1542	-.1219	-.0227**	-.1181

NB All correlations are statistically significant at the 1% level unless indicated with a * (statistically significant at the 5% level) or a ** (not statistically significant at the 5% level).

Key:

PLWEER90	Proportion of elective episodes with a long waiting time, specialty R (routine surgery) 1990-91
STWTEG90	Standardised waiting time, specialty G (gynaecology) 1990-91
OWN_OCC	Proportion of persons living in owner-occupied accommodation
NO_CAR	Proportion in households with no car
OVER_CROWD	Proportion in households in crowded accommodation
BLACK	Proportion in Black ethnic group
OLD_ALONE	Proportion of those of pensionable age living alone
ONE_CARER	Proportion of dependents in single carer households
PERM_SICK	Proportion of adult population permanently sick
STUDENTS	Proportion of working age population who are students
UNEMPLOY	Proportion of economically active that are unemployed
MANUAL	Proportion of persons in households with head in manual class
SIRI074	Standardised illness ratio for those aged under 75
SMR074	Standardised mortality ratio for those aged under 75
NEED	Weighted index of health needs

APPENDIX 3: THE INSTRUMENT SETS

Given below are the variables used as instruments in the 2SLS equations reported in the main body of the text.

	Equation description				
	Demand	Supply	Elective	Length of stay	Day cases
Tables	15,16, 20,22	17-19, 21,23	27	26	25
Instruments					
WAIT_TIME90	✓			✓	
DAY_CASES90		✓	✓	✓	
ELECTIVES90		✓			
LENGTH_STAY90		✓	✓		
NEED	✓				
A11				✓	✓
A12		✓	✓	✓	✓
A21			✓	✓	✓
A22			✓	✓	✓
A23				✓	✓
A31	✓	✓	✓	✓	✓
A41	✓		✓	✓	✓
A51		✓	✓	✓	✓
A52		✓	✓	✓	✓
A53	✓	✓		✓	✓
A54			✓	✓	✓
A55				✓	✓
A61				✓	✓
A62		✓	✓	✓	✓
A71		✓	✓	✓	✓
A72		✓	✓	✓	✓
A73	✓	✓	✓	✓	✓
A74		✓		✓	✓
A75	✓	✓	✓	✓	✓
A76		✓	✓	✓	✓
A771		✓	✓	✓	✓
A78	✓	✓	✓	✓	✓
A81IN		✓	✓	✓	✓
A82		✓	✓	✓	✓
A91		✓	✓	✓	✓
A92		✓	✓	✓	✓
A101			✓	✓	✓
A102		✓	✓	✓	✓
LONGILL		✓			
SIRI074		✓	✓	✓	✓
SIRI75	✓	✓	✓	✓	✓
SMR074		✓	✓	✓	✓
SMR75	✓	✓	✓	✓	✓
A121			✓	✓	✓
A131	✓	✓	✓	✓	✓
A141	✓	✓	✓	✓	✓
A142		✓	✓	✓	✓
A143	✓	✓	✓	✓	✓
A144	✓	✓			✓
A145		✓		✓	✓
A151			✓	✓	✓
A171			✓	✓	✓
A181	✓	✓	✓	✓	✓
PCTURBAN		✓	✓	✓	✓
PBIR	✓	✓	✓	✓	✓
DVB-DVP		✓	✓	✓	✓

Instrument Set Key:

WAIT_TIME90	Standardised waiting time, 1990-91
DAY_CASES90	Proportion of electives treated as day cases, 1990-91
ELECTIVES90	Proportion of admissions that are elective
LENGTH_STAY90	Standardised (for age and sex) length of stay
NEED	Weighted combination of A62, A71, A121, SIRI074 and SMR074 (see below for details of these variables).

Tenure

A11 Proportion of residents in permanent buildings which are owner occupied
A12 Proportion of residents in permanent buildings which are privately rented

Amenities

A21 1-(Proportion of residents in households lacking or sharing use of bath/shower and/or inside WC)
A22 Proportion of residents in households lacking central heating
A23 1-(Proportion of residents in households in non-self-contained accommodation)

Car ownership

A31 Proportion of residents in households with no car

Overcrowding

A41 Proportion of residents in households with crowded accommodation, that is, with more than one person per room

Ethnic origin

A51 Proportion of residents in households with head born in New Commonwealth
A52 Proportion of residents in non-white ethnic groups
A53 Proportion of residents born in the New Commonwealth
A54 1-Proportion of residents in black ethnic groups
A55 1-Proportion of residents in Indian, Pakistani and Bangladeshi groups

Elderly living alone

A61 Proportion of those aged 75+ living alone
A62 Proportion of those of pensionable age living alone

Lone parents

A71 Proportion of dependents in single carer households
A72 Proportion of persons in lone parent households
A73 Proportion of children in lone parent families
A74 1-Proportion of families with economically inactive lone parent
A75 1-Proportion of families with lone parent and dependent children
A76 Proportion of children in non-earning lone parent families
A771 Proportion of children in non-earning families
A78 Proportion of dependents in no carer households

Permanently sick

A81IN Proportion of residents of working age permanently sick (standardised)
A82 Proportion of adult population permanently sick

Students

A91 Proportion of 17 year olds who are students
A92 Proportion of working age population who are students

Migrants

A101 Proportion of residents moving from outside local authority district in the last year
A102 Proportion of residents who have a different address to that one year ago

Limiting long-term illness

LONGILL Proportion of total population with a limiting long term illness
SIRI074 Standardised illness ratio for those in households aged 0-74
SIRI75 Standardised illness ratio for those in households aged 75+
SMR074 Standardised mortality ratio - ages 0-74
SMR75 Standardised mortality ratio - ages 75+

Unemployment

A121 Proportion of the economically active that is unemployed

Qualifications

A131 Proportion of persons aged 18+ with some qualification

Social class

A141 Proportion of persons in households with head in class 1 or 2
A142 Proportion of persons in households with head in manual class
A143 Proportion economically active residents in 1 and 2
A144 Proportion economically active residents in manual
A145 Proportion economically active residents in non-manual

Other

A151 1-Proportion of families that are concealed

A171 Population density
A181 Proportion of those aged 75+ living in residential/nursing homes
PCTURBAN Proportion of population living in urban enumeration districts
PBIR Proportion of live births (where weight recorded) weighing < 2.5kg
DVB-DVP Regional dummy variables