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Rationing by time, distance and money in the NHS: variations in admission rates

Hugh Gravelle* Mark Dusheiko* Matthew Sutton*

Abstract. We construct a model of the determinants of the rate of admission of patients from general practices for elective surgery in public sector hospitals where public patients face positive waiting times and distance costs but a zero money price. The model is tested with data on general practice admission rates for cataract procedures in an English Health Authority. We find that admission rates are negatively related to waiting times and distance to hospital. Practices respond to budgetary incentives: fundholding practices have lower admission rates than non-fundholders; admission rates fall less for fundholders than for non-fundholders when waiting times increase and fall by less for fundholders than for non-fundholders as patients have a higher propensity to opt for the private sector.

Keywords: fundholding; waiting times; distance; admission rates; general practice.
JEL Nos: I11, H51

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1. Introduction

The British National Health Service (NHS) is a tax financed compulsory insurance system with universal coverage. No charges are made to patients for hospital care. There is no rationing of emergency care, which is typically accessed directly via hospital accident and emergency departments. To receive non emergency or elective hospital care, which accounts for about half of the 8 million NHS annual admissions, patients must be referred by their general practitioner (GP).

The most obvious features of the system are the large stock of patients waiting at any time and the long waits for elective secondary care. Over 1 million patients were waiting for elective surgery in 1996 in England. The average waiting time over all specialities in England was 111 days in 1997/8 and the average for patients in our data set on cataracts procedures in a large Health Authority was 245 days. The saliency of waiting lists has made them a focus of political debate and a variety of policy measures aimed at reducing them have been introduced. Such policies have not been conspicuously successful (Harrison and New, 2000).

This paper contributes to the understanding of the way care is rationed in the NHS through time and money prices by examining the decision making of a key set of players: the GPs who are the gatekeepers between primary and secondary elective care. We address two specific issues of policy relevance. The first is the extent to which the rate of admission for patients from general practices is affected by waiting time. When there is excess demand for elective care and more patients are added to waiting lists than are being treated the waiting list grows and waiting times increase. Conversely when there is excess supply. The responsiveness of demand to the waiting time price determines the extent to which the waiting time price must change to clear the market and the change in the number of patients waiting. The elasticity of demand with respect to waiting time is therefore a crucial piece of policy information. The more elastic is demand the more expensive it will be to reduce waiting times by increasing the supply of care. If demand is elastic an increase in supply will lead to a fall in waiting time but will an increase in the number waiting.

The second issue is how GPs respond to the financial incentives in the NHS budgetary system. Almost all GPs are independent contractors, rather than employees of the NHS. Their income is determined by the difference between the revenue their practice receives from the NHS and the costs they incur. Until April 1991 the costs of elective care for a practice's patients were borne by the local Health Authority (HA). GPs had no financial incentives to take account of such costs when deciding whether to refer patients. After April 1991 practices were able to apply to hold a budget, allocated by their HA, to cover the cost of a range of elective procedures for the patients on their lists. If practices spent less than their budget they were allowed to spend the surplus on improving the health care of their patients in other ways. The scheme gave practices an incentive to reduce referrals since they might feel that the other types of health care they could purchase were of more value to their patients. In many cases "improving the health care" was interpreted to mean investment in practice premises. Since many practices owned their premises, they also had a direct financial interest in reducing referrals to earn a surplus. Fundholding was not universal, so that by comparing the admission rates of fundholding and non-fundholding practices we can investigate the responsiveness of practices to the imposition of budgets for care.

Fundholding was abolished in April 1999 but may hold lessons for the system of Primary Care Groups which replaced it. A typical Primary Care Groups covers the populations of around 20 practices with a total population of about 100,000 patients and holds a unified budget to cover almost all types of NHS expenditure, including secondary care. It is intended (Department of Health, 1997) that Primary Care Groups will introduce practice budgets linked to financial incentives whereby practices are permitted to spend savings on improving care for their patients.

Although there is a large literature on waiting lists and waiting times (Cullis, Jones and Propper, 2000; Harrison and New, 2000) there is relatively little quantitative evidence on the effect of waiting times on demand for health care and that is generally at a highly aggregate level. Martin and Smith (1999) used cross section data on elective admission rates for 4460 synthetic wards England in 1991/2 and estimated that the elasticity of demand with respect waiting times was -0.20. In Gravelle, Smith and Xavier (2000) the elasticity of demand with respect to waiting time was estimated to be -0.30 using a panel of quarterly data on district health authorities from 1987 to 1993. The key decision makers in a system like the NHS are the gatekeeping GPs who decide whether to refer patients to hospital specialists for further investigation and possible admission. We have found no studies of the impact of waiting times on admissions using practice level data.

The bulk of the evidence to date is that fundholding status does not make any difference to referral rates (Goodwin, 1998; Coulter and Bradlow, 1993; Hippisley-Cox et.al., 1997; Whynes and Baines, 1996). Croxson, Propper and Perkins (2000) proposed a new test based on the argument that fundholders increased referral rates in the year before they become fundholders in order to get a larger budget and reduced them thereafter. Using a data similar to ours they found that such fundholder gaming effects did occur.

The current paper makes two contributions. First it present a simple formal model of the admission process and uses it to guide the estimation of practice admission rates. The model is an extension of previous models (Lindsay and Feigenbaum, 1984; Smith and Martin, 1998) in that it allows for GPs to make imperfect assessments of the benefits from treatment so that not all referred patients are admitted by the hospital.

Second, our paper uses a new data set of practice admission rates derived from the Contract Minimum Data Set (CMDS) for all the practices in a large northern Health Authority. Croxson, Propper and Perkins (2000) have used a similar data set for a different HA and our study is complementary to theirs. Because we focus on the admissions for a single procedure (cataracts) rather than examining rates aggregated over procedures our data are more subject to random variation and we are unable to test for fundholders gaming the system by comparing annual rates. However, we have richer data on patient socio-economic conditions and practice characteristics. More importantly, we have calculated waiting times for practice patients and therefore able both to allow for the effect of waiting times when examining the effects of fundholding and to estimate the responsiveness of admissions to waiting times at practice level.

Section 2 sets out the model of practice admission rates and derives predictions of the effects of patient and practice characteristics. Section 3 describes the data and discusses its limitations. Section 4 describes the estimation of the model and the results. Section 5 discusses the implications of the results.

2. Modelling admission rates

The aim of this section is to outline a simple but reasonably plausible account of the admission process. We use it to derive the estimating equation used in the empirical work and to assist in the interpretation of results.

There are three stages to the admission process for non emergency surgery in the NHS: the patient develops symptoms and consults their GP, the GP decides whether to refer the patient to an outpatient clinic to be seen by a hospital consultant and the consultant decides whether to place the patient on the waiting list for elective surgery. Since the focus is on the GP's referral decision we treat the decision rules of consultants as exogenous and unaffected by the behaviour of individual practices. We also assume that the probability of a patient consulting with symptoms which may merit referral is exogenous.

GPs are assumed to be quasi-altruists: their referral decisions reflect their estimates of the benefits and costs of referral for the patient but they also take account of the effort costs and financial implications for the practice. The GP knows the distribution of benefits $F^0(b)$ from the operation for patients who consult. (We suppress the dependence of F^0 on the characteristics of the practice population for the time being.) When a patient consults the GP makes an imperfect observation of the benefit for the patient of $\boldsymbol{b} = b + e$, where the error e has zero mean and distribution function $G(e)$. The GP's posterior distribution of benefits for the patient is $F^1(b; \boldsymbol{b})$.

Consultants are specialists and better able to estimate a patient's benefit from treatment than the GP. Assume that if the patient is referred the consultant makes a perfect assessment of the benefit from the operation. The consultant has an admission threshold and admits all referred patients whose benefit exceeds b^k

The patient incurs costs of c_{pr} if referred and, if the consultant decides to place them on the waiting list, will wait t months before being admitted. (Any costs incurred by the patient as a result of the operation are netted out of the benefit.) The GP incurs costs of c_{gr} if the patient is referred. If the patient is admitted the GP may also bear further costs for post discharge care of admitted patients. In addition, a fundholding practice will have to pay for the operation out of its budget. Denote the sum of these operation costs as c_{ga}.

The GP is semi-altruistic and perceives the expected benefit from referring the patient to be

$$v^1 = \boldsymbol{d}(t)\int_{b^k}^{\infty}(b - sc_{ga})\,dF^1(b; \boldsymbol{b}) - c_{pr} - sc_{gr} \tag{1}$$

where s is a parameter reflecting the degree of selfishness of the GP. Entirely altruistic GPs have $s = 0$ and are influenced only by the costs and benefits to the patient. $d(t)$ is the discount factor and is decreasing and strictly convex in t.

The GP refers all patients for whom v^1 is positive. Since a higher observed $\mathbf{b}$ shifts the entire posterior distribution to the right, v^1 is increasing in $\mathbf{b}$ and the GP's decision rule can be equivalently stated in terms of a referral threshold. All patients for whom $\mathbf{b} \geq \mathbf{b}^*$ are referred, where $\mathbf{b}^* = \mathbf{b}^*(s, c_{ga}, t, c_{pr}, c_{gr}, b^k)$ is defined by $v^1 = 0$. The referral threshold is increasing in the waiting time, patient costs, practice referral costs, and practice admission costs. More altruistic practices (with lower s) have a lower referral threshold.

Since all patients for whom $\mathbf{b} = b + e \geq \mathbf{b}^*$ are referred the referral rate is

$$R = \mathbf{p}\int_{-\infty}^{\infty} \left[1 - G(\mathbf{b}^* - b)\right] dF^0(b) = R(\mathbf{b}^*; \mathbf{p}), \quad R_{b^*} < 0, \quad R_p > 0. \tag{2}$$

and the admission rate is

$$A = \mathbf{p}\int_{b^i}^{\infty} \left[1 - G(\mathbf{b}^* - b)\right] dF^0(b) = A(\mathbf{b}^*(s, c_{ga}, t, c_{pr}, c_{gr}, b^k), b^k, \mathbf{p}) \tag{3}$$

where $\mathbf{p}$ is the exogenous probability that a patient consults with relevant symptoms.

Figure 1 illustrates (ignore the line b^* for the time being). All patients seen by the GP are characterised by their true benefit and the error the GP makes in observing them. All patients with (b, e) above the line $b + e = \mathbf{b}^*$ are referred. The consultant admits those for whom $b \geq b^k$ so that admitted patients are those above the $\mathbf{b}^*$ locus and to the right of b^k.

The comparative static effects of the parameters in the model are straightforward. and intuitively plausible. $A(\mathbf{b}^*, b_k, \mathbf{p})$ is decreasing in the referral threshold $\mathbf{b}^*$ and hence is decreasing in waiting time, practice and patient costs and increasing in the practice's degree of altruism. The direct effect of an increase in the hospital admission threshold b^k, which directly reduces the admission rate, is reinforced by its indirect effect in raising the referral threshold.

Fundholding practices had higher costs c_{ga} per patient admitted since they paid for the admission from their budget, whereas the patients of non fundholding practices were paid for by their Health Authority. There is some evidence (Propper, Croxson and Shearer, 2000) that fundholding patients had shorter waits t. It is also possible that hospitals had different admission criteria for fundholding patients which would be reflected in the model through the consultant admission threshold b^k. We assume that individual fundholding practices were too small relative to providers to influence the price charged to fundholders, the waiting times or the admission criterion for fundholding patients. Fundholders were in effect contract takers, though they could shop around for the best contract. Since fundholders had higher admission costs but possibly lower waiting times their admission rates for a single procedure, which is what we have data on, may be higher or lower than for non fundholding practices. We have data on the waiting times for practice patients though not on consultant admission policies. Assuming that b^k does not differ greatly for patients of fundholding and non-fundholding practices, we can test the prediction that, for given waiting times, the financial incentives of holding a budget and bearing the charge for admission leads to lower admission rates.

We have neglected two aspects of the admission process which we cannot incorporate in our estimated model because of lack of data. We now examine their implications for the interpretation of the estimation results.

There is delay between referral and the patient being assessed in the outpatient department. Such delays may be of the order of several weeks. Allowing for such delays, the expected net benefit from referral is

$$v^2 = d(t+t_o)\int_{b^k}^{\infty}(b - sc_{ga})dF^1(b;\mathbf{b}) - d(t_o)[sc_{go} + c_{po}] - c_{pr} - sc_{gr} \tag{4}$$

where t_o is the wait to be seen in the outpatient department. c_{go} and c_{po} are the costs of outpatient attendance for practice and patient. Increases in t_o reduce both the benefits and costs of referral but v^2 decreases in t_o for convex discount functions. The referral threshold b^* is therefore increasing in t_o, so that the referral rate and the admission rate are decreasing in the outpatient waiting time.

We have data on the time the patient waits after being put on the waiting list for elective surgery by the consultant but not on the wait from referral to outpatient visit. If the waiting times for outpatient appointments and for admissions are correlated the estimated effect of the delay from outpatient appointment to admission will be biased. Suppose that the supply of outpatient appointments and the supply of operations at a hospital are fixed and equal to S^o and S respectively. Summing across all practices which use the hospital, the total number of referrals and admissions are $D^o(t,t_o,\cdot)$ ($D_1^o < 0, D_2^o < 0$) and $D(t,t_o,\cdot)$ ($D_1 < 0, D_2 < 0$) respectively. The market for outpatient appointments and operations is cleared when $D^o(t,t_o,\cdot) = S^o$ and $D(t,t_o,\cdot) = S$. The equilibrium waiting times are functions of the supply of both appointments and operations and the factors affecting the referral decisions of practices.

Assuming that the market is well behaved,[1] supply shocks induce negatively correlated changes in the waiting times. For example, after an increase in the number of outpatient clinics a reduction in the outpatient waiting time is required to increase the number of referrals. The resulting increase in the number of people placed on the waiting list for admissions must be choked off by an increase in the time they will wait on the list for operations. Demand shocks which increase the propensity of GPs to refer patients induce positive correlation in outpatient and operation waiting times. There is no reason why demand or supply shocks should be dominant in our data set. Our estimates of the effect of waiting times after the patient is placed on the list for elective surgery are unlikely to be biased by the effect of the omitted outpatient waiting times.

[1] The determinant of the system must be positive: $D_1 D_2^o - D_2 D_1^o > 0$.

We also interested in the effect of fundholding status on practice admission rates and here the lack of information on outpatient waiting times may be more of a problem. If fundholding practices have contracts with providers who have shorter outpatient waiting times then estimates of the effect of fundholding status on admission rates will reflect some of the effect of shorter outpatient waiting times and will be biased upward. We suspect that the bias will not be great because waits for outpatient appointments are much shorter than those for the operation itself and are likely to exhibit less variation. If the estimated effect of fundholding is negative, positive omitted variable bias strengthens the implication that fundholders have fewer patient admitted.

The second feature we have neglected so far is private practice: patients can choose to pay for private treatment, which has a much shorter waiting time, rather than waiting for NHS treatment. About 1/6th of elective procedures are funded privately, either via private medical insurance or self financed. NHS consultants are permitted to work both in the NHS and in the private sector and patients often get their operation from the same surgeon, irrespective of whether they have waited on the list as NHS patients or whether they have opted to pay the surgeon to perform the operation privately with a shorter wait.[2] Assume that patients, whether they will eventually go private or whether they will remain in the NHS, consult their GP and are referred to the consultant. Suppose that the consultant applies the same clinical criteria in deciding whether to recommend an operation irrespective of whether the patient will go private or remain an NHS patient. After the consultant has determined that $b \geq b_k$ the patient decides whether to be put on the NHS waiting list and be treated after a delay of t or to pay c_{pm} for immediate private treatment. The patient will opt for private treatment if $d(t)b \leq b - c_{pm}$ so that all patients with a benefit exceeding $b^* = b^*(c_{pm}, t) = c_{pm}/(1-d(t))$ prefer to be treated privately.

The GP is aware of the possibility that a referred patient may opt for private care on learning her benefit from the operation. The expected benefit from referral is perceived by the GP as[3]

$$v^3 = d(t)\int_{b^k}^{b^*}(b - sc_{ga})dF^1(b;b) + \int_{b^*}^{\infty}(b - c_{pm} - sc_{gm})dF^1(b;b) - c_{pr} - sc_{gr} \quad (5)$$

where c_{gm} are the costs borne by the practice if the patient is admitted privately. The GP referral threshold is now

$$b^* = b(s, c_{ga}, c_{gm}, t, c_{pm}, c_{pr}, c_{gr}, b^k, b^*(c_{pm}, t)) = b^*(s, c_{ga}, c_{gm}, t, c_{pm}, c_{pr}, c_{gr}, b^k) \quad (6)$$

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[2] It has been alleged that some consultants make their NHS patients wait longer in order to increase the proportion who will want to be treated privately (Yates, 1995). This will not affect the specification of our model provided that fundholders act as contract takers and regard the waiting times of private patients, fundholding practice patients and non-fundholding practice patients as given.

[3] If patients have different b^* which are known to the GP, for example because they have private medical insurance, there will be different referral thresholds for different types of patient. The practice referral and admission rates will be the sum of the rates for the different types of patient.

With the possibility of private treatment there are now four relevant groups of patients as shown in Figure 1: those who are not referred, those referred but not treated, those referred and treated in the NHS and those referred who are treated privately.

An increase in b^* changes the expected benefit from referral at the rate

$$v^3_{b^*} = [\delta(t)(b^* - sc_{ga}) - (b^* - c_{pm} - sc_{gm})]f^1 = -\delta s(c_{ga} - c_{gm})f^1 \qquad (7)$$

where $f^1(b^*; \beta^*)$ is the posterior density of patient benefits. If patients are less likely to opt for private treatment (higher b^*) the practice will refer fewer of them if it incurs higher costs from an NHS admission than a private admission: $c_{ga} > c_{gm}$.

Practice follow up costs for patients who receive the operation may not differ greatly between NHS and private sector operations but fundholders are charged for NHS operations. If the difference between c_{ga} and c_{gm} is negligible for non-fundholders, a reduction in the propensity of patients to go private (an increase in b^*) will have no effect on their referral rates but will raise the referral threshold for fundholders: $\beta^*_{b^*} = -v^3_{b^*} / v^3_b > 0$.

However, we do not observe the referral rate but only the practice rate of admissions for publicly funded (NHS) treatment

$$A^3 = \pi \int_{b^k}^{b^*} [1 - G(\beta^* - b)]dF^o(b) = A^3(s, c_{ga}, c_{gm}, t, c_{pm}, c_{pr}, c_{gr}, b^k, \pi) \qquad (8)$$

The effect of an increase in the threshold for going private is

$$\frac{\partial A^3}{\partial b^*} = \pi \left\{ [1 - G(\beta^* - b^*)] f^o(b^*) - \beta^*_{b^*} \int_{b^k}^{b^*} g(\beta^* - b)dF^o(b) \right\} \qquad (9)$$

The increase in the threshold for going private increases the probability that a referred patient is admitted for NHS treatment but it may reduce the referral rate. In Figure 1 although b^* shifts to the right, $b + e = \beta$ may shift upward so that the effect on admissions is ambiguous.

Since the referral threshold for fundholders exceeds that for non-fundholders the first term in the braces in (9) is smaller for fundholders than non fundholders. We expect $\beta^*_{b^*} = -v^3_{b^*} / v^3_b$ to be small or zero for non fundholding practices and positive for fundholders. Hence, fundholding practices will have a smaller increase in the admission rate in response to an increase in the propensity of their patients to go private.

We cannot measure b^* directly, nor do we have information on the extent of private health care insurance which we would expect to lead to lower b^*. We attempt to test whether fundholding practices react differently to differences in propensity to seek private care by examining interactions between fundholding status and proxies for propensities to take out private insurance affect admission rates. The expectation is that a reduction in b^* (due to larger private insurance coverage) causes a smaller reduction in admissions of NHS patients for fundholding than for non-fundholding practices. The coefficient on the interaction between fundholding status and proxies for private health insurance is predicted to be positive.

The effect of an increase in waiting times on NHS admission rates is

$$\frac{dA^3}{dt} = \frac{\partial A^3}{\partial b^*} b_t^* - b_t^* \int_{b^k}^{b^*} (g(b^* - b) dF^0 \qquad (9)$$

Longer waits drive more people into the private sector given that they are referred: the first term in (9) is negative since $b_t^* < 0$. The increase in waiting times also increases the threshold for referrals which tends to reduce waiting times. Stability in the market requires that the overall effect of an increase in waiting times is to reduce admission rates, so the second effect dominates the first.

We argued above that the first term in (9) is greater absolutely non-fundholders than for fundholders. Comparison of the second term across fundholders and non fundholders requires very detailed information on values of parameters and shape of the posterior, prior and error distributions. However the analysis suggests a further test for whether GPs respond to the financial incentives of fundholding: are interaction effects between fundholding status and waiting times significant?

There is some evidence that waiting times for elective care influence the extent of private medical care insurance (Besley, Hall and Preston, 1996). If $c_{pm} = c_{pm}(t)$, then (9) must be augmented by the change in insurance status and thus the price of private care. However, we are interested in the overall effect of t, not in its decomposition. This is true even if patients believe that fundholding practices get shorter waiting times from providers, so that patients of such practices are *ceteris paribus* less likely to hold private health insurance. The possible correlation of fundholding status with the unobserved extent of private insurance will not bias estimates of the effect of fundholding status on admission rates since the correlation arises via the waiting time, which is included in our estimating equation. Estimating the reduced form effect of waiting time will suffice.

3. Data

The variables are described in Table 1. The main data source is the Health Authority's Contract Minimum Data Set (CMDS). It includes only patients who were registered with a HA general practice, and resident inside the HA border. Each record represents a completed consultant spell for patients receiving cataract and other eye operations (OPCS category C). Patients are matched to their practice, treatment provider and consultant. The data set covers a 3 year period (April 1995 to March 1998) and consists of 8048 individual patient admissions from 109 GP practices to 13 different providers. The CMDS also records the patient's age, gender, date placed on the waiting list for the procedure and date admitted.

Details about practices and their list's characteristics were obtained from the HA and the Attribution Data Set (ADS). Information on GP practices included their list size at June

1998, the number of whole time equivalent GPs per practice, the age and gender of the GPs, and the opening hours of the practice. There is also information on whether the practice was a fundholder and the year (wave) in which they became a fundholder. Practice lists contained the number of patients of each sex in 22 age bands. We used the information in the ADS to subtract the number of non HA residents in every age and gender band to make practice list sizes comparable with the episode data. No adjustment for practice level list inflation (duplicate NHS registrations, and deaths that are not removed) could be made.

The ADS contains 1991 census information on 16 variables aggregated to synthetic ward levels. The variables measure mortality, morbidity and socio-economic status (see Table 1), and were found to be significant need adjusters by Carr Hill et al (1994) when deriving the national resource allocation formulae for secondary care expenditure. The census characteristics were assigned to practices by taking a weighted average of synthetic ward values, where the weights were the proportion of a practice's resident and registered population living in a particular ward.

The use of aggregated census data means our inference is susceptible to the ecological fallacy, since the patients in a given ward from a practice are not random samples from the population of the ward (Carr-Hill and Rice, 1995). The measures of mortality, morbidity and deprivation in the ADS reflect general health needs. They may not be sensitive measures of the incidence or prevalence of visual acuity problems correctable by cataract procedures (Gray et al., 1999).

Straight line and road distances between each practice and every cataract provider used by HA practices was calculated using postcodes and grid references. Individual patient postcodes were unavailable. Attributing distances to patients on the basis of the practice they belong to is most likely to be a problem for analysis using individual admissions as the dependent variable. Our model is of practice admission rates. If the average patient to provider distance is not too different to the distance from practice to provider the implications of using an attributed distance measure should not be too serious.

Practice cataract admission rates were directly standardised by aggregating the practice specific age and sex strata rates after weighting them by the strata specific rates of the HA's resident and registered population.

4. Estimating the demand for admissions

Estimating equation

The estimating equation for the model in section 2 is determined by the availability of the data usable as proxies for the explanatory variables and is

$$A = A(W, G, D, T, Z, M, u) \tag{4}$$

We do not have information on the prices paid by individual practices for fundholding procedures and attempt to capture the effects of fundholding with a set of dummy variables W.

G are other practice characteristics such as the average age of GPs, their gender balance, the number of patients per GP in the practice, and practice opening times. The literature suggests that a number of characteristics of practices can influence consultation, referral and admission rates, including list size per GP (Croxson, Propper and Perkins, 2000), experience of GPs (Reynolds, Chitnis and Roland, 1991), and single handed status, though the impact of the latter factor on referrals has been found to be negative in one study (Hippisley-Cox et.al., 1997) and positive in another (Whynes and Baines, 1996).

Such factors may affect the accuracy of GPs assessment of patient benefits, or alter the propensity of patients to consult, thereby shifting the distribution of benefits. Or practices with more patients per GP may be more likely to refer to shift the burden of patients to the secondary sector or take less care in making their initial assessments.

Patients have to bear the travel and inconvenience costs of visits for outpatient assessment and treatment if admitted. We proxy such costs by measures of distance *D* from the practice to providers and expect that greater distances result in a lower admission rate. We have information on the waiting times of practice patients and use it to construct indicators *T* of the waiting time. Longer waits are predicted to reduce admission rates for non fundholders and fundholders.

Socio economic characteristics *Z* of practice patients are also expected to influence admission rates. Previous studies have found that consultation, referral and admission rates have been shown to vary with a number of socio-economic characteristics of practice populations (Campbell and Roland, 1996; Carr-Hill, Rice and Roland, 1996) including age, sex, measures of deprivation, access to car, education and social class. For example, patients with their own cars may have lower costs of attending outpatient clinics. Morbidity measures *M* shift the distributions of benefit from treatment.

Estimating the model of practice admission rates raised a number of issues. The substantive implications of the results are discussed in section 5.

Variable selection

The last two columns of Table 1 show the log odds model with all variables included.[4] Although none of the population socio-economic characteristics are individually significant we were able to reject the null hypothesis that they have no combined effect on admission rates. We also examined the four practice characteristic variables (age, gender mix, GPs per head of practice population and practice opening hours). None were individually significant and they were also not jointly significant.

To select a parsimonious model highly collinear variables were dropped if they had a large variance inflation factors (VIF)

[4] As heterscedasticity is a potential problem with pooled cross-sectional data robust standard errors were estimated for the reported regressions here and in the other tables. Except where stated, all regressions weight observations by the number of patients resident in the HA.

$$VIF_j = \frac{1}{1 - R_j^2}$$

where R_j^2 is the coefficient of determination from a regression of the *j*'th explanatory variable on all the other explanatory variables (Maddala, 1992). Most of the remaining variables were included if they were individually significant or significant when included with other variables. A backwards stepwise procedure, dropping the least significant variables first, produces the same set of variables with the exception of *hpsick* which is jointly significant with the *sir* variables. Although the practice characteristic variables were generally insignificant, *gpage* is retained in the model as it has a *t*-ratio greater than unity and increases the goodness of fit of the model. The final set of variables is shown in Table 2.

Distance measures

We experimented with a number of aspects of the distance measure: straight line versus road distance, distances to all providers, to the providers used by a practice and to the nearest provider only, weighted (by practice or HA use) distance versus unweighted distance, and linear versus non linear (logarithmic) distance The choice of distance measure made very little difference to the pattern of coefficients on the other variables and only a small difference to the overall performance of the equation. The preferred measure is *wroadkm*: the mean road distance from the practice to all potential providers weighted by the admissions to the providers from all the HA practices.

Functional form

Two main alternative functional forms were compared: the linear and the log-odds in which the dependent variable is the log of the odds of admission for a patient drawn at random from the practice. Columns 1 and 2 of Table 2 compare the estimated equations for the log odds and the linear models. Both models perform reasonably well in terms in the proportion of the total variation explained and yield similar patterns of significance and signs on coefficients. The linear model has more significant coefficients and a higher R squared adjusted for degrees of freedom.

The Ramsey Reset test does not suggest any obvious problems with either model. The P_E test (Maddala, 1992) results (not shown) were formally inclusive. We were very close to rejecting the null hypothesis of a linear form (p = 0.0614), whereas we failed to reject the null hypothesis of a log odds form by some margin.[5]

The dependent variable in the linear and log-odds specifications is the practice admission rate and the explanatory variables are also at practice level. Since there is data on the age and sex structure of the practice populations and the age and sex characteristics of the admitted patients from a practice it is possible to estimate a grouped logistic model using individual level data. The model was estimated using frequency weights for the number of individuals admitted from each age and sex strata in a particular practice. Age and sex effects were included as dummy explanatory variables.

[5] We also attempted to compare the linear and log odds specification with a full set of explanatory variables, rather than the set used Table 2. This was not possible because of insufficient variation in the fitted values.

The difference between the log odds and the grouped logistic specifications is primarily in the treatment of the effects of age and sex on admission probabilities. The practice level log odds model uses a directly standardised admission rate as the dependent variable and imposes a particular type of assumption about the effect of age and sex on admission probabilities. The grouped logistic model allows the data to determine how age and sex affect admissions.

Column 3 of Table 2 reports the grouped logistic regressions. The coefficients on all but one of the age category variables were, unsurprisingly for cataracts procedures, highly significant. The coefficient on gender was also highly significant, indicating that men have a lower admission probability. The reported coefficients are very similar to those from the log odds model. More coefficients are significant at conventional levels because of the much greater number of observations. Since the focus in the study is on the practice level admission rate we use the log odds model rather than the individual level grouped logistic.

Measurement of waiting times

The waiting time for practice patients was measured as the median waiting time rather than the mean. The main issue with the waiting time variable was missing data on waiting times for around 25% of the patients admitted. The deficiency was almost entirely attributable to one large provider which had missing waiting time data on 75% of its cataract admissions. There appeared to be no systematic pattern to the missing information

We estimated waiting times for patients by regressing the waiting time of patients on their characteristics, their practice and their provider. The details of the regressions and the method are available on request. We compared three different approaches to the waiting time measure (see Table 2). Column 4 uses the actual waiting times on the patients for whom we had data to calculate practice waiting times (*wait*). Column 5 uses predicted waiting times for all patients (*fitwait*). Column 1 uses predicted waiting times for patients with missing waiting time data and the actual waiting time for the other patients (*mixwait*). Parameter estimates are similar across models but *mixwait* has a greater adjusted R^2 (0.35) and a more significant coefficient on the waiting times variable ($p = 0.004$).

Exogeneity of waiting times

We assumed in section 2 that waiting times for practice patients are not affected by the demand for admissions from the practice population. The assumption seems reasonable in the context of a model of the demand for admissions at practice level. Any single practice accounts for a small proportion of the total demand at any given provider and so the waiting times of patients from the practice are not affected by demand from the practice. If the waiting time is endogenous the coefficient on practice waiting times in the estimating equation will be biased towards zero. Table 2 shows that the results from using the estimated waiting time (*fitwait*) are very similar to those from our preferred model in column 1, suggesting that endogeneity of practice waiting times is not a problem.

Fundholding status

After April 1991 practices could opt to become fundholders and there were seven annual waves. (See Table 1.) The data covers three years from April 1995 – March 1996 to April

1997 – March 1998, so wave 5 practices became fundholders in the first year of our data, wave 6 in the second year and the single wave 7 practice was a fundholder only in the third year.

Table 3 compares several specifications of the fundholder effect. Column 1 reproduces the results from column 1 of Table 1 and shows the effect of being a particular wave fundholder compared with not being a fundholder. Column 2 distinguishes between "early" fundholders (waves 1 to 5) and "late" fundholders (waves 6 to 7). The results are broadly similar results to those in column 1. The early fundholder effect is significant but the late fundholder effect is not. This is not surprising since any fundholder effect operated only in years 2 and three for wave 6 and year 3 for wave 7. Column 1 has a large and significant wave 1 effect but no other significant effect, though all the other early fundholder wave coefficients are negative. Column 3 has an even less detailed measure: a single fundholding dummy which indicates if the practice was or was not ever a fundholder. The coefficient on the dummy is negative but insignificant, probably because the weaker effects for later waves dilute the stronger effects for early fundholders.

Column 4 is similar to column 1 but does not weight the observations on practices by their practice list size. Since early fundholding practices were larger than late fundholders and non fundholders the unweighted regression in column 4 puts less emphasis on the fundholding effects of early fundholders. As a consequence none of the fundholding dummy variables have significant coefficients and indeed some of the coefficients are positive.

The minimum practice list size requirements for fundholding were relaxed over time to encourage the spread of fundholding **(**Le Grand, Mays and Mulligan, 1998)**.** Column 5 investigates whether the size of the practice list (*netlist*) accounts for the difference between first wave fundholders and non-fundholders. The variable is insignificant and first wave fundholders still have significantly lower admission rates. We conclude that the first wave fundholder effect is not explained by differences in practice size.

Practices could decide whether and when to become fundholders so that it is likely that the fundholding status is correlated with unobservable characteristics of the practice and its GPs (Baines and Whynes, 1996). To allow for possible endogeneity bias we estimated an ordered logit model of choice of fundholding wave (detailed results are available on request). We used the predicted probabilities of being a wave 1, wave 2 etc fundholder in the admission rate equation instead of the wave 1, wave 2 dummies. The results are shown in column 6 of Table 3. Wave 1 fundholding has significant effects in both specifications. The signs of the some of the coefficients on the other waves are different but are not significant in either specification. The experiment suggests that the fundholding effects are not strongly contaminated by the endogeneity of fundholding status.

Three year versus single year rates

Our main modelling exercise was based on aggregating all admissions for a practice over the three years from April 1995 to March 1998. From the date of admission of each patient it is possible to calculate yearly admission rates and to analyse the resulting data set using panel data techniques. It would generally be sensible to use such techniques since they allow for year effects and may be able to identify dynamic effects, such as the effect of a change in fundholder status.

There are two potential problems with using the approach with the current data set. First, admissions for cataracts are a rare event so that annual admission rates are very small (the HA annual rate is 36.5 per 10,000 patients). The variation in observed admission rates across practices is in part due to purely random factors and in part to genuine systematic differences in the practice rates (McPherson et al, 1982). Dividing the data into years increases the importance of purely random factors and tends to obscure any genuine practice effects (Moore and Roland, 1989). Second, the only explanatory variables which vary over time are practice waiting times and whether the practice is a fundholder (and the latter variable only changes for the wave 6 and 7 fundholders).

We experimented with specifications in which the dependent variable was the practice admission rate in a year, rather than the admission rate over three years. Table 4 reports the results of estimating a log odds random effects panel data model. (One practice was dropped from the estimation since it had no admissions in one year.) The first set of results are for the log odds model without yearly dummies and the other two show the effects of including yearly dummies, with the third set allowing for varying year to year correlation of practice residuals.

The results show that yearly effects matter since the coefficients on the year dummies are significant and the first equation is misspecified according to the Reset test. The substantive results are similar to those from the three year model although there are more significant fundholder effects and the waiting time coefficient is not significant, though it is negative in all variations.

Croxson, Propper and Perkins (2000) argue that fundholders had an incentive to increase admissions in the year before they became fundholders in order to increase their budgets for succeeding years. We attempted to test for such dynamic fundholder effects with a panel data model including interaction terms between fundholding wave and year dummies. Although the results (available on request) were similar to our other models, the wave-year interactions were not significant. The lack of significance may be due to our data relating to a single procedure so that random fluctuations in yearly admission rates swamp any systematic dynamic effects, and to the small number of wave 6 and 7 fundholders.

Fundholder interaction effects

For reasons set out in section 2, fundholders and non-fundholders will respond differently to changes in waiting time. Fundholders will also reduced their admission rates by more in response to an increase in the propensity to go private. We proxy the propensity by the level of educational qualifications in the practice population, and expect more qualified patients to be more likely to go private. Columns 1 to 4 of Table 5 report experiments with interactions between fundholding status and waiting time or qualifications. (There is no interaction term for wave 7 because there was only one wave 7 fundholder.) Including the interactions generally does not change the pattern of coefficients or their significance on other terms. The model in column 1 with both sets of interactions with a full set of wave dummies fails the

RESET test but the remaining models appear not to be misspecified. The interactions between fundholding status and waiting times are usually positive and are significant for wave 1 (columns 1, 2, and 4) or the early fundholding dummy (column 3). The interactions between fundholding status and qualifications are also generally positive but fewer are significant.

Additions versus admissions

The model in section 2 suggests that practices' rates of referral are affected by their fundholding status at the date of referral. We have data on admissions, rather than referrals. We know (or can estimate) the waiting time for individual patients and can calculate the rate at which patients from a practice are added to the waiting list in any given period and are admitted within the three years. We have no information on patients added to the list in the three years but admitted after the end of year 3. The median waiting time is 248 days and so we attempted to avoid the selection bias which would arise in calculating practice rates of addition in years 2 and 3 by calculating the rate of addition of patients placed on the list in year 1 and admitted in the three year period.

Regressions using a log odds model of additions had low explanatory power with adjusted R^2 of around 0.10 and few significant coefficients, though the sign patterns were similar to models using admissions as the dependent variable. Models with fundholder interactions with waiting time and qualifications had much higer explanatory power, had similar sign and significance patterns to additions models but failed RESET tests. Column 5 in Table 5 reports a linear additions model with interactions of fundholder status waiting time and qualifications. The sign pattern is similar to other interaction models in the table but many more coefficients are significant. The model fails the RESET test though nothing like as badly as the log odds models with additions or with admissions with both sets of interactions. The addition rate is based on data for one year only and are therefore more likely to be influenced by random than systematic factors than the admission rate based on three years of data.

Summary

The comparisons in this section show that the results discussed in the next section are robust across a wide variety of alternative assumptions and approaches:

- elimination of insignificant variables made little to magnitude of the coefficients on the final reduced set of explanatory variables
- the choice of distance measures does affect the significance on the coefficients on distance and waiting times but our preferred measure, which yields significant coefficients and has greater explanatory power, is also more justifiable on theoretical grounds
- linear, log odds and grouped logistic models yield similar results
- alternative measures of waiting time made little difference to results
- measurement of fundholding status - treating all waves of fundholding together did not show significant effects of fundholding but there was a significant effect when early and late fundholders were distinguished
- allowing for endogeneity of waiting times and fundholding status made little difference to the results

- pooled versus annual rates - use of three separate yearly rates rather than a three yearly average rate reduces the significance of the coefficients on the waiting time variable but does not alter the basic pattern of results
- addition of interactions between fundholding and waiting times or qualifications did not alter the pattern of results on other terms
- models with additions to the list as the dependent variable have much lower explanatory power than models with admissions

5. Discussion

We have specified and estimated a model of the demand by practices for elective care for their patients. It addresses two main issues in the determinants of the demand for elective care in the NHS: can waiting time act as a market clearing mechanism in that increases in waiting time reduce demand and do practices respond to the incentives created by giving them fixed budgets?

Socio-economic characteristics of practice populations

The initial full model included set of 16 socio economic characteristics of the practice populations derived from the 1991 Census. Very few were individually significant and the only socio-economic characteristic included in the final models was the percentage of the population with A-level qualifications or better. The coefficient on the education variable is negative and significant and the odds ratio in Table 2 shows that an increase of one percentage point in the population who are highly educated is associated with a 2.1% reduction in the admission rate. Since it is plausible that more highly educated patients are more likely to seek eye examinations (Schaumberg et al, 2000) the finding is puzzling. One possible explanation is that education is correlated with some unobserved measure of good visual health. Another is that education is positively correlated with wealth and the propensity to seek private treatment, so that the rate of NHS admission is lower in practices with more highly educated populations.

Morbidity

The model includes two measures of morbidity: the percentage of the population who were permanently sick (*hpsick*) and the standardised illness ratio for those aged less than 75 (*sir074*). The effects of the morbidity measures were often offsetting so that interpretation is difficult. For example in column 2 of Table 2, increases in the percentage who were permanently sick are associated with a higher admission rate which seems intuitively plausible. The negative coefficient on *sir074* and the positive coefficient on its square indicate that the relationship with admissions is U-shaped. The bottom of the U occurs at a *sir074* value of about 100. The mean *sir074* for HA practices is 86 so that for the HA as a whole an increase in the standardised illness ratio would be associated with a reduction in admissions, though the effects are small. The results suggest that the available morbidity measures are not sensitive indicators of visual acuity problems.

Distance

The effect of distance on admissions is intuitively plausible and in line with previous findings (Carr-Hill, Place and Posnett, 1997, Croxson, Propper and Perkins 2000; Hippisley-Cox and Pringle, 2000). Increases in the distance between practices and providers have significant and negative impacts on admission rates in almost all specifications. The odds ratio in Table 2 indicates that an increase of 10km in the average distance to providers is associated with a 1/20th reduction in the admission rate. Alternatively, evaluating results of the model at the average value of the variables across HA practices, the elasticity of admissions with respect to distance is -0.35.

Waiting times

Increases in waiting times have the predicted expected negative effect on admission rates and the estimated coefficients on the waiting time measures is nealry always significant. In Table 2, the elasticity of admissions with respect to waiting time is -0.25. This is similar in magnitude to estimates obtained by Smith and Martin (1998) and Gravelle, Xavier and Smith (2000) using different national level data sets on all elective admissions. The results suggests that waiting time has a crucial role in rationing elective care and functions as a market clearing mechanism.

Fundholding status

Fundholding status was the only characteristic of practices which was systematically associated with admission rates. In almost all specifications early wave fundholders had lower admission rates than later fundholders and non fundholders. The effects were also large. For example in Table 2 the odds ratio indicates that being a patient of a wave 1 fundholding practice reduces the probability of admission by about one third. Moreover, the effect is still present after allowance has been made for the endogeneity of fundholding.

Fundholders also reduce their admission rates by less than non-fundholders when waiting times increase. The interactions between fundholding status and qualifications are also generally positive as predicted by the model of section 2. The findings emphasise the importance of allowing both for the direct effects of socio economic factors and waiting times and their interaction with fundholding status.

The results contrast with most of the literature reported in the review by Goodwin (1998). They extend and support the findings of Croxson, Propper and Perkins (2000) since they are based on a separate but similar database for a different Health Authority and estimate the effect of fundholding after allowing for the influence of waiting times and socio economic factors on admissions. The evidence from our more recent studies which use larger and richer data sets is that fundholding does reduce admission rates and that fundholding and non-fundholding practices respond differently to changes in their environment, particularly waiting times. In short, GPs did respond to the financial incentives implicit in a budget for patient care.

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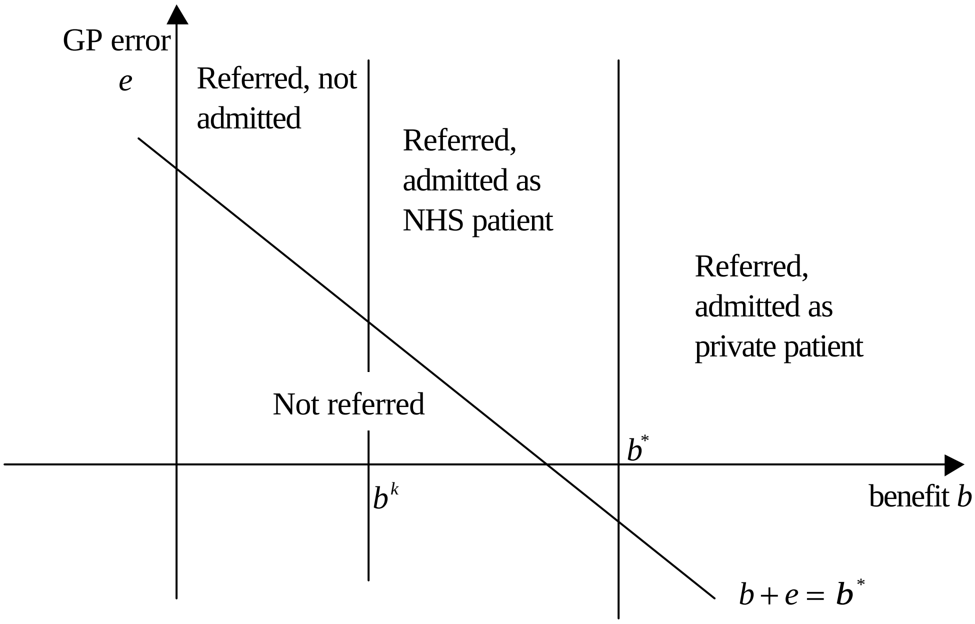

Figure 1. Referrals and admissions. GP referral threshold: b^*, consultant admission threshold: b^k, patient threshold for private admission: b^*.

Table 1 Descriptive statistics (population weighted) and full model

Variable	Description	Mean	SD	Min	Max	Full model (logodds) coeffic	p value
Wave1	Wave 1 fundholder dummy	0.12	(0.05 unweighted)			-0.332	[0.035]*
Wave2	Wave 2 fundholder dummy	0.09	(0.05 unweighted)			-0.177	[0.182]
Wave3	Wave 3 fundholder dummy	0.15	(0.13 unweighted)			-0.032	[0.771]
Wave4	Wave 4 fundholder dummy	0.06	(0.06 unweighted)			-0.119	[0.231]
Wave5	Wave 5 fundholder dummy	0.22	(0.24 unweighted)			-0.087	[0.394]
Wave6	Wave 6 fundholder dummy	0.05	(0.06 unweighted)			0.002	[0.992]
Wave7	Wave 7 fundholder dummy	0.01	(0.01 unweighted)			-0.094	[0.381]
		Mean	**SD**	**Min**	**Max**		
Gphead	WTE GPs per person on list	5.68	0.90	3.33	14.03	-0.008	[0.856]
Femgp	Proportion of female practice GPs	0.28	0.16	0	1.00	0.120	[0.520]
Gpage	Mean age of practice GPs	43.36	3.27	34.50	64.00	0.016	[0.145]
Gphours	Weekly practice surgery hours	45.37	24.21	0	108.75	-0.001	[0.602]
Wroadkm	Average distance from practice to all cataract providers, weighted by proportion of HA admissions	54.55	14.06	39.23	116.35	-0.090	[0.048]*
Mixwait	Median practice waiting times (days), missing values estimated	248.25	69.27	107.00	393.00	-0.068	[0.004]**
Hncenh	Percent of households without c.h.	20.31	7.00	8.07	39.50	-0.053	[0.541]
Newcom	Percent of residents born in New Commonwealth	0.84	0.31	0.36	2.46	0.039	[0.891]
Hnocar	Percent of households with no car	27.25	8.16	10.82	49.11	-0.004	[0.915]
Smr074	SMR for under 75s (1989 - 1993)	92.32	8.68	72.00	114.84	0.002	[0.800]
Unempl	Percent of economically inactive residents	5.42	1.77	2.95	10.85	-0.068	[0.267]
Hhnewc	Percent of household residents born in New Commonwealth	1.01	0.43	0	1.94	-0.163	[0.451]
Scarer	Percent of dependants with a non-dependent carer	17.60	2.67	11.77	24.60	-0.065	[0.318]
Sir074	Standardised limiting long term illness ratio for the under 75s	86.36	9.54	61.92	108.04	-0.007	[0.657]
Hchild	Percent of households with more than three children	4.30	0.69	2.78	7.79	0.098	[0.317]
Dncare	Percentage of dependants with a dependent carer	14.80	3.25	5.95	25.82	0.035	[0.365]
Studnt	Percentage of working age residents who were students	5.32	0.92	3.85	9.12	0.022	[0.756]
Qualfd	Percentage of residents aged over 18 with 'A' level qualifications	15.56	3.76	8.01	30.37	-0.020	[0.312]
Rswdiv	Percentage of single/widowed/divorced residents	50.27	2.88	44.64	58.39	-0.007	[0.887]
Tpsick	Percent of adult population unable to work because of permanent illness	3.08	0.59	1.94	4.40	-0.098	[0.428]
Hpsick	Percent of household adults not working due to permanent sickness	2.72	0.52	1.78	4.22	0.503	[0.068]
Lnpens	Percent of pensionable age living in single person households	32.71	2.98	26.82	40.44	-0.007	[0.859]
Lnpare	Percent of households with only one member aged over 16	6.92	2.29	1.96	13.00	0.108	[0.212]
Adjrate	Practice cataract admission rate, directly standardised	36.54	12.33	8.47	80.36		
					Const:	-4.841	[0.029]*
					Adj R^2	0.25	
					Reset	Pr > F = 0.109	

Table 2. Comparison of functional forms and waiting time measures

	0 Odds ratio (from col 1)	1 logodds	2 linear	3 grouped logistic	4 logodds	5 logodds
Wave1	0.674	-0.394 [0.022]*	-13.126 [0.003]**	-0.45 [0.000]**	-0.368 [0.035]*	-0.4 [0.021]*
Wave2	0.890	-0.116 [0.103]	-6.677 [0.014]*	-0.19 [0.000]**	-0.126 [0.126]	-0.124 [0.104]
Wave3	0.954	-0.047 [0.545]	-3.548 [0.212]	-0.16 [0.001]**	-0.042 [0.599]	-0.05 [0.515]
Wave4	0.868	-0.141 [0.057]	-7.176 [0.004]**	-0.199 [0.000]**	-0.15 [0.048]*	-0.139 [0.067]
Wave5	0.983	-0.113 [0.191]	-5.451 [0.069]	-0.155 [0.000]**	-0.108 [0.231]	-0.13 [0.126]
Wave6	1.060	0.058 [0.635]	0.915 [0.835]	0.008 [0.872]	0.074 [0.555]	0.075 [0.543]
Wave7	0.981	-0.019 [0.772]	-2.858 [0.207]	-0.101 [0.385]	-0.004 [0.960]	0.004 [0.951]
gpage	1.010	0.01 [0.303]	0.322 [0.291]	0.006 [0.085]	0.011 [0.260]	0.01 [0.332]
wroadkm	0.942	-0.006 [0.007]**	-0.208 [0.001]**	-0.006 [0.000]**	-0.006 [0.009]**	-0.007 [0.005]**
mixwait	0.970	-0.001 [0.004]**	-0.059 [0.001]**	-0.002 [0.000]**		
wait					-0.001 [0.034]*	
fitwait						-0.002 [0.008]**
sir074	0.943	-0.059 [0.096]	-2.806 [0.012]*	-0.068 [0.002]**	-0.073 [0.054]	-0.068 [0.063]
sir2	1.000	0.0001 [0.138]	0.016 [0.019]*	0.00039 [0.002]**	0.000 [0.081]	0.000 [0.108]
qualfd	0.979	-0.021 [0.026]*	-0.812 [0.014]*	0.137 [0.008]**	-0.02 [0.039]*	-0.024 [0.013]*
hpsick	1.174	0.16 [0.171]	6.72 [0.088]	-0.019 [0.000]**	0.183 [0.135]	0.207 [0.095]
Age dummies				chi2(20) = 7275 [0.000]**		
Male				-0.235 [0.000]**		
Constant		-2.788 [0.105]	171.547 [0.001]**	1.428 [0.146]	-2.425 [0.190]	-2.302 [0.188]
Observations		109	109	731888	109	109
Adjusted or pseudo R^2		0.3456	0.4465	0.27	0.318	0.33
Reset test		Pr>F = 0.457	Pr>F = 0.223	Pr>chi2 = 0.056	Pr>F = 0.375	Pr>F = 0.107

* Significant at 5% level; ** significant at 1% level.
The unit of distance in column 0 is 10kms and 1 km in cols 1 to 5; the unit of mixwait in col 0 is 30 days (1 month) and 1 day in cols 1 to 5.

Table 3. Comparison of different fundholding specifications

	1	2	3	4	5	6
	logodds	logodds	logodds	logodds (unweighted)	logodds	logodds (fitted wave probabilities)
Wave1	-0.394			-0.329	-0.491	-0.518
	[0.022]*			[0.122]	[0.043]*	[0.041]*
Wave2	-0.116			-0.028	-0.183	0.369
	[0.103]			[0.727]	[0.101]	[0.403]
Wave3	-0.047			0.12	-0.071	0.277
	[0.545]			[0.234]	[0.401]	[0.709]
Wave4	-0.141			0.017	-0.144	-1.067
	[0.057]			[0.860]	[0.046]*	[0.803]
Wave5	-0.113			0.058	-0.116	0.088
	[0.191]			[0.562]	[0.187]	[0.978]
Wave6	0.058			0.174	0.058	2.438
	[0.635]			[0.191]	[0.634]	[0.940]
Wave7	-0.019			0.111	-0.025	-8.815
	[0.772]			[0.184]	[0.708]	[0.960]
Earlywave		-0.164				
		[0.039]*				
Latewave		-0.063				
		[0.395]				
Anywave			-0.126			
			[0.069]			
Gpage	0.01	0.011	0.011	0.009	0.011	0.011
	[0.303]	[0.249]	[0.234]	[0.359]	[0.278]	[0.213]
Wroadkm	-0.006	-0.006	-0.006	-0.003	-0.006	-0.006
	[0.007]**	[0.022]*	[0.028]*	[0.196]	[0.006]**	[0.011]*
Mixwait	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001
	[0.004]**	[0.005]**	[0.006]**	[0.004]**	[0.004]**	[0.007]**
Sir074	-0.059	-0.079	-0.087	-0.052	-0.058	-0.064
	[0.096]	[0.070]	[0.053]	[0.290]	[0.091]	[0.084]
Sir2	0.001	0.001	0.001	0.001	0.0003	0
	[0.138]	[0.110]	[0.080]	[0.378]	[0.138]	[0.121]
Qualfd	-0.021	-0.023	-0.023	-0.033	-0.019	-0.023
	[0.026]*	[0.013]*	[0.011]*	[0.009]**	[0.033]*	[0.015]*
Hpsick	0.16	0.238	0.204	0.167	0.183	0.214
	[0.171]	[0.027]*	[0.048]*	[0.254]	[0.110]	[0.036]*
Netlist					0.00850	
					[0.428]	
Constant	-2.788	-1.903	-1.563	-2.997	-2.992	-2.797
	[0.105]	[0.374]	[0.481]	[0.197]	[0.073]	[0.120]
Obs	109	109	109	109	109	109
Adjusted R^2	0.3456	0.296	0.2883	0.2733	0.345	0.382043
RESET test	Pr>F = 0.46	Pr>F = 0.36	Pr>F =0.43	Pr>F = 0.10		Pr>F = 0.02

Robust p - values in brackets. * significant at 5% level; ** significant at 1% level
Col 6 uses estimated probs of practice being wave 1, wave 2 etc. fundholder

Table 4. Random effects panel estimates (yearly practice admission rates)

	1		2		3	
	logodds	odds ratio	logodds	odds ratio	logodds	odds ratio
Wave1	-0.41683	0.659	-0.41207	0.662	-0.40057	0.669
	[0.01]*		[0.01]*		[0.01]*	
Wave2	-0.09743	0.907	-0.09194	0.912	-0.09421	0.910
	[0.19]		[0.23]		[0.22]	
Wave3	-0.08227	0.921	-0.08091	0.922	-0.07791	0.925
	[0.27]		[0.29]		[0.28]	
Wave4	-0.16266	0.850	-0.16791	0.845	-0.16619	0.847
	[0.02]*		[0.02]*		[0.02]*	
Wave5	-0.15942	0.853	-0.1615	0.851	-0.15269	0.858
	[0.04]*		[0.04]*		[0.05]	
Wave6	0.05838	1.060	0.06379	1.066	0.0626	1.065
	[0.66]		[0.63]		[0.62]	
Wave7	-0.00091	0.999	0.00357	1.004	-0.00098	0.999
	[0.99]		[0.96]		[0.99]	
Wdistkm	-0.00677	0.935	-0.0064	0.938	-0.00668	0.935
	[0.01]*		[0.02]*		[0.01]**	
Ymixwait	-0.00075	0.977	-0.00049	0.985	-0.00055	0.983
	[0.11]		[0.26]		[0.21]	
Gpage	0.00431	1.004	0.00433	1.004	0.00424	1.004
	[0.61]		[0.60]		[0.60]	
Sir074	-0.09047	0.914	-0.10098	0.904	-0.09843	0.906
	[0.01]*		[0.01]**		[0.01]**	
Sir2	0.00054	1.001	0.0006	1.001	0.00058	1.0005
	[0.01]*		[0.01]**		[0.01]**	
Qualfd	-0.01737	0.983	-0.01777	0.982	-0.01871	0.981
	[0.05]		[0.06]		[0.04]*	
Hpsick	0.09531	1.100	0.09819	1.103	0.11327	1.119
	[0.34]		[0.34]		[0.25]	
Year2			0.16415	1.178	0.16304	1.177
			[0.00]**		[0.00]**	
Year3			0.27915	1.322	0.27864	1.321
			[0.00]**		[0.00]**	
Constant	-1.5177	0.219216	-1.29842		-1.364318	0.256
	[0.38]		[0.45]		[0.42]	
Observations	324		324		324	
Number of practices	108		108		108	
RESET tests	Pr > chi2 = 0.006		Pr > chi2 = 0.492		Pr > chi2 = 0.488	

Semi-robust p - values in brackets
(model 3 allows for time varying within practice correlation)
* significant at 5% level; ** significant at 1% level

Table 5: Comparison of models with and without fundholder interactions for waiting times and education

	(1)	(2)	(3)	(4)	(5)
	logodds	logodds	logodds	logodds	addrate
Iwaves_1	-5.996		-2.0156	-1.464	-219.411
	[0.006]**		[0.032]*	[0.297]	[0.000]**
Iwaves_2	-0.113		-0.318	-0.139	-28.053
	[0.859]		[0.105]	[0.667]	[0.017]*
Iwaves_3	-0.913		-0.491	-0.589	-45.717
	[0.041]*		[0.114]	[0.039]*	[0.024]*
Iwaves_4	-1.177		-0.649	-0.653	-88.941
	[0.040]*		[0.093]	[0.097]	[0.000]**
Iwaves_5	-0.981		-0.751	-0.568	-63.894
	[0.078]		[0.038]*	[0.112]	[0.002]**
Iwaves_6	-0.298		-0.058	-0.228	8.910
	[0.458]		[0.870]	[0.613]	[0.577]
Iwaves_7	-0.0014		-0.0001	0.0015	-0.069
	[0.719]		[0.672]	[0.754]	[0.000]**
early		-0.957			
		[0.003]**			
late		-.166			
		[0.626]			
gpage	0.009	0.006	0.005	0.011	0.543
	[0.455]	[0.523]	[0.606]	[0.304]	[0.164]
wroadkm	-0.004		-0.004	-0.006	-0.009
	[0.022]*		[0.008]**	[0.010]**	[0.860]
mixwait	-0.002	-0.003	-0.003	-0.001	-0.066
	[0.000]**	[0.000]**	[0.000]**	[0.020]*	[0.003]**
sir074	-0.049	-0.100	-0.055	-0.043	-0.070
	[0.274]	[0.044]*	[0.126]	[0.373]	[0.352]
sir2	0.0003	0.001	0.0002	0.0002	0.0003
	[0.386]	[0.076]	[0.230]	[0.404]	[0.515]
qualfd	-0.038	-0.039	-0.021	-0.041	-0.370
	[0.022]*	[0.013]*	[0.047]*	[0.016]*	[0.064]
hpsick	0.245	0.271	0.250	0.138	0.444
	[0.109]	[0.014]*	[0.053]	[0.276]	[0.009]**
IwXmix_1	0.01		0.007		0.453
	[0.035]*		[0.064]		[0.000]**
IwXmix_2	0.003		0.001		0.028
	[0.393]		[0.369]		[0.697]
IwXmix_3	0.002		0.002		0.040
	[0.167]		[0.120]		[0.319]
IwXmix_4	0.002		0.002		0.177
	[0.099]		[0.136]		[0.030]*
IwXmix_5	0.002		0.003		0.128
	[0.065]		[0.039]*		[0.001]**
IwXmix_6	-0.001		0.0002		-0.168
	[0.899]		[0.915]		[0.047]*
IeXmix_1		0.002			
		[0.017]*			
IlXmix_1		-0.001			
		[0.738]			
IwXqua_1	0.205			0.067	5.633745
	[0.002]**			[0.461]	[0.003]**
IwXqua_2	-0.054			0.001	0.971
	[0.589]			[0.977]	[0.516]
IwXqua_3	0.031			0.035	1.810

	[0.069]			[0.048]*	[0.032]*
IwXqua_4	0.029			0.031	1.983
	[0.217]			[0.200]	[0.004]**
IwXqua_5	0.02			0.030	1.594
	[0.327]			[0.163]	[0.073]
IwXqua_6	0.027			0.020	1.513
	[0.651]			[0.423]	[0.225]
Constant	-2.775	-0.174	-2.464	-3.239	42.043
	[0.196]	[0.943]	[0.168]	[0.164]	[0.157]
Observations	109	109	109	109	109
Adjusted R-squared	0.409	0.334	0.393	0.329	0.344
RESET tests	Prob > F = 0.0014	Prob > F = 0.2169	Prob > F = 0.4819	Prob > F = 0.2850	Prob > F = 0.0420

Robust p-values
significant at 5% level; ** significant at 1% level
For regression (5) the waiting time variable is the median practice waiting time of individuals added to the list in the period April 1995 to March 1996.