IDENTIFYING DEMAND FOR HEALTH RESOURCES USING WAITING TIMES INFORMATION

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SUMMARY

In this paper we utilise the differences in average waiting times to identify the determinants of demand for health services. We use the equilibrium waiting time framework but relax the full equilibrium assumption by selecting areas with low waiting times and estimating a (semi-)parametric selection model. Determinants of supply are used as instruments for the endogeneity of waiting times. We estimate a model for the demand for acute services at the ward level in the UK. We contrast our model estimates, and their implications for health service allocations in the UK, to more standard allocation models. Our results show that it is critically important to account for rationing by waiting times when identifying needs from care utilisation data.

JEL Classification: C14, C51, I10

1. Introduction

The aim of this paper is to consider the specification and estimation of a statistical model for health care utilisation. Our model draws on the recent literature that relates waiting times to the demand and supply of services (see Lindsay and Feigenbaum (1984), Gravelle (1990) and Goddard et al. (1995), for example). In this model waiting time acts as a hassle cost to treatment and in equilibrium the waiting time costs will be just sufficient to reduce demand to equal the supply of services. For example, suppose there is an increase in demand, waiting times will increase. Some individuals already on the list will drop out and others who had thought of joining will not join. Similarly for a change in supply. Waiting time essentially plays the role of a price, with people looking for alternative care, possibly private, or no care at all when the waiting time becomes too long. Provided waiting times adjust fairly rapidly then this equilibrium framework seems reasonable. Martin and Smith (1999) use this model to estimate demand and supply models for elective surgery in the UK and find that waiting time is indeed negatively correlated with demand.

The standard equilibrium waiting time approach rests on two assumptions: 1. the observed data are in equilibrium; 2. waiting times accurately measure waiting time costs. Both assumptions may be strong and are not necessary for the central approach taken in this paper. If there is a higher than expected demand then we still observe supply but demand and waiting times may not have adjusted to equilibrium, this is equivalent to the min{demand, supply} condition in standard disequilibrium models (see Gourieroux, Laffont and Monfort, 1980). Our approach is to select areas in which the waiting times are reasonably low and use these to estimate the determinants of demand. This approach is therefore robust to disequilibrium in high waiting time areas and reduces the sensitivity to systematic measurement error in the tails of the waiting time distribution. Our aim is limited, simply to recover characteristics that influence demand for health services at low waiting time costs. The objective is not to estimate a model of both demand and supply but rather to examine the determinants of demands, or needs, abstracting from distortions caused by supply side constraints in health care provision. We use the determinants of supply as instruments for the waiting time to correct for the potentially endogenous selection of low waiting times areas in which services may be more likely to reflect demand. However, we do contrast our results with those for the standard equilibrium specification for demand.

The model we use is based on a regression specification for normalised level of health care utilisation. It is precisely this kind of model that is used in the allocation of NHS funds in the UK (see Smith et al. (1994)), and our application is to the demand for acute hospital care at the local (ward) level in the UK. We introduce the idea that some wards may be supply constrained so that a regression on needs variables alone on the whole sample will not correctly identify demand parameters. Instead we suggest the use of average waiting time by ward as an indicator of supply rationing. We use wards with relatively low waiting times to capture demand when the time costs of waiting are low. Even within the equilibrium waiting time framework of Lindsay and Feigenbaum (1984) this still seems a good idea since at high waiting times, the waiting time variable will surely interact in quite a complicated way with needs variables. For example, suppose at low waiting times richer young people place a high demand on resources but drop out if there are high time costs, then at high waiting times the income and age effects will be different.

Our choice of areas with low waiting times implies that there will be few people who came on the list from the past and who thus reflect demands from earlier periods. Added to this we are worried about systematic reporting bias in the waiting time variable, as there are obvious incentives for providers to under-report high waiting times, and that this variable may not be a good measure of waiting time costs. Also if individual demands are nonlinear in waiting time then the aggregate demand in a ward will not depend only on the average waiting time (as Martin and Smith (1999) point out there are many measures of waiting time). However, we do also estimate a simple parametric model that includes the waiting time variable as an endogenous determinant of demand and show that when selecting wards with reasonable low levels of waiting times this variable does not appear to influence demand. This contrasts dramatically with the results for higher waiting time areas where waiting time is found to be a strongly significant determinant of demand.

The central specification we estimate is a selection model that estimates needs variables for wards that have an average waiting time below some specified cut off. Since the model estimates are likely to be sensitive to parametric distributional assumptions we check the robustness of our results using semiparametric selection methods in estimation (see Newey, Powell and Walker ,1990). The fact that we have a number of excluded supply side variables that strongly determine waiting times and have a wide variation across the data makes this application well suited to the use of semiparametric selection methods.

The rest of the paper is organised as follows. In section 2 we develop the model and section 3 presents the data and estimation results. As the important outcome of the demand model is the actual resource allocations over the regions, we also look at the impact of the various estimation procedures on the estimated regional need indices. Section 4 concludes.

2. Model and Estimation

2.1. An Empirical Specification of the Demand for Services

Let O_i represent the outflow rate from a particular medical service in ward i and I_i represent the corresponding inflow rate onto the service register for that ward. In any given ward in a given time period the waiting time, W_i, will be a function of current and past net inflow rates. There may exist a waiting time W_i^* at which the two rates are equilibrated

$$I_i = O_i \Leftrightarrow W_i = W_i^*.$$

In this framework the waiting time acts like a price of services, reducing demand as W_i rises. Demand for services will depend on characteristics of the local population $\mathbf{x}_i^d$ (needs variables), the waiting time level W_i and unobservables u_i^d

$$y_i^d = f(\mathbf{x}_i^d, W_i) + u_i^d. \tag{2.1}$$

The inflow rate will be directly related to y_i^d. Therefore W_i and y_i^d will be simultaneously determined.

Two approaches are available for estimation. One could assume a parametric form for (2.1), for example

$$y_i^d = \boldsymbol{\beta}'\mathbf{x}_i^d + \gamma W_i + u_i^d, \tag{2.2}$$

and estimate directly. However, note that since W_i is endogenous to demand a suitable instrument will be required. An obvious choice of instrument would be some determinant of supply. However, current fluctuations in supply could be correlated with unobservables in demand. A safer instrument would be a lagged supply variable, or lagged waiting times. We discuss particular choices in the empirical application below. Martin and Smith (1999) estimate demand equation (2.2) within a full equilibrium model.

A number of potential difficulties arise with this approach. First, it is likely that reported waiting time levels W_i, especially at the upper end of the distribution, are likely to be systematically biased. Secondly, it is likely that when waiting times are long, the waiting time variable will interact in quite a complicated way with the needs variables. Thirdly, at low waiting time levels, say below W^m, it is less likely that W_i will influence demand. Given that the aim of this paper is rather modest - to evaluate the importance of different needs variables, not to estimate the impact of W_i on demand directly - we take a slightly different, and hopefully more robust, approach. We specify that demand for services takes the form

$$y_i^d = \boldsymbol{\beta}'\mathbf{x}_i^d + u_i^d \text{ for } W_i < W^m, \tag{2.3}$$

where W^m will be in the lower quantiles of the observed waiting time distribution. To check whether W_i does indeed not influence demand at low levels of waiting times, we also estimate (2.3) with W_i included in the model. We further check the robustness of our results to different choices of cut-off point W^m.

Even in this approach endogeneity arises in estimating (2.3). In particular there is endogenous selection on W_i which in turn depends on demand for services through the net inflow rate. Therefore using this framework, the demand parameters β can be identified from the wards with low average waiting time, while taking care of the endogenous selection rule. If W^m is known, standard (semi-)parametric techniques can be applied, utilising limited information on the average waiting times in the sense that only the information whether W_i is larger or smaller than W^m is used. As we argued above, the waiting time information is likely to be subject to systematic measurement error especially towards the upper tail. Consequently the use of the limited information will reduce the impact of this measurement problem.

2.2. An Approach to Estimation

The estimators we utilise in this paper for the standard selection model are a parametric two-step estimator (Heckman (1979)), and a semi-parametric estimator as proposed by Robinson (1988). The first step in estimation is to specify a binary indicator for the average waiting time:

$$\begin{aligned} w_i &= 1 \quad if \quad W_i \geq W^m \\ w_i &= 0 \quad if \quad W_i < W^m. \end{aligned}$$

This is assumed to follow some simple linear index probability model

$$\Pr[w_i = 1] = \Pr[\boldsymbol{\pi}'\mathbf{z}_i + \varepsilon_i \geq 0]$$

Under normality, the parameters π/σ_ε, where σ_ε is the standard deviation of ε, can be consistently estimated by the standard Probit maximum likelihood estimator. The standard Heckman (1979) two-step estimator specifies the model of demand for services in wards with low waiting times as

$$\begin{aligned} y_i^d &= \boldsymbol{\beta}'\mathbf{x}_i^d + E\left[u_i^d | W_i < W_i^m\right] + \eta_i^d \\ &= \boldsymbol{\beta}'\mathbf{x}_i^d + \lambda \frac{\phi\left(\boldsymbol{\pi}'\mathbf{z}_i/\sigma_\varepsilon\right)}{1 - \Phi\left(\boldsymbol{\pi}'\mathbf{z}_i/\sigma_\varepsilon\right)} + \eta_i^d, \end{aligned}$$

where $\lambda = -\sigma_{u^d\varepsilon}/\sigma_\varepsilon$, and $\sigma_{u^d\varepsilon}$ is the covariance of u^d and ε , which are assumed to be jointly normally distributed. The two-step procedure then amounts to substituting the probit estimate $\widehat{\pi/\sigma_\varepsilon}$ for π/σ_ε, and estimating the parameters β and λ by OLS.

Given the initial estimate for π/σ_ε, the semi-parametric estimator of Robinson (1988) proceeds as follows. Let $v_i = \boldsymbol{\pi}'\mathbf{z}_i/\sigma_\varepsilon$, then the conditional model can be written as

$$y_i^d = \boldsymbol{\beta}'\mathbf{x}_i^d + g\left(v_i\right) + \xi_i^d,$$

where $g(.)$ is some unknown function. Subtracting the conditional expectation of y_i^d given v_i results in

$$y_i^d - E\left[y_i^d|v_i\right] = \boldsymbol{\beta}'\left(\mathbf{x}_i^d - E\left[\mathbf{x}_i^d|v_i\right]\right) + \xi_i^d, \tag{2.4}$$

which is no longer a function of $g(v_i)$, and OLS estimation of (2.4) gives consistent and asymptotically normal estimates for $\boldsymbol{\beta}$ (excluding the constant). The conditional means $E\left[y_i^d|v_i\right]$ and $E\left[\mathbf{x}_i^d|v_i\right]$ are estimated non-parametrically using kernel regressions. The kernel estimator of $E[x|v=c]$ is a weighted average of x for v in the neighbourhood of c, given by (see e.g. Härdle and Linton (1994))

$$\widehat{E}_h[x|v=c] = \frac{\frac{1}{N}\sum_{i=1}^{N} K_h(c-v_i)\,x_i}{\frac{1}{N}\sum_{i=1}^{N} K_h(c-v_i)},$$

where

$$K_h(c-v_i) = \frac{1}{h}K\left(\frac{c-v_i}{h}\right),$$

K is a *kernel* function which is continuous, bounded and symmetric and which integrates to one, and h is a bandwidth parameter decreasing with sample size N. In estimating (2.4) using kernel regressions to estimate the conditional mean terms, some trimming may be required to remove areas of the data where the density of v is too sparse.

3. Data and Estimation Results

The data for the estimation of the models as described in section 2 are the same data as have been used by Smith et al. (1994) for the construction of the allocation formula of NHS revenues. In their work, the final needs regression results are based on the hospital utilisation of all wards. The waiting times data are the same as in Martin and Smith (1999).

The dependent utilisation variable is the standardised estimated costs of acute care in 1991-92 (ACCOS91). The waiting time data are the average numbers of days waited for routine surgery in 1991-92 (WT91). Supply and demand variables are measured in 1990-91. In the timing of the utilisation we differ from the approach of Smith et al. (1994). In their study the utilisation variable was the average utilisation per ward in the years 1990-91 and 1991-92, and the supply variables had to be instrumented. We avoid the problem of endogeneity by using lagged values of the supply measures.

Table 1 gives descriptions and summary statistics of the variables we use in this study. For a further description and guide to the construction of these variables see Martin (1994), Carr-Hill et al. (1994) and Martin and Smith (1999). As can be seen from the table, the average waiting time for routine surgery in 1991-92 is 117 days. There are four supply variables, namely NHS hospital accessibility (ACCNHS), general practitioner accessibility (ACCGP), the proportion of the 75 years and older *not* in nursing and residential homes (HOMES*), and private hospital accessibility (ACCPRI). The needs variables considered are the standardised mortality ratio-ages 0-74 (SMR074), a standardised illness ratio-ages 0-74 (HSIR074), the proportion of persons in manual class (MANUAL), the proportion of persons of pensionable age living alone (OLDALONE), the proportion of dependants in single carer households (S_CARER), the proportion of the economically active that are unemployed (UNEMP), and the proportion of residents in households with no car (NOCAR). Table 1 also reports summary statistics for those wards that have waiting times less than 100 days, and that will be used in our estimation of the demand equation (2.3) below. The average waiting time in these wards is 86 days. The summary statistics of the other variables in the selected sample are all very similar to those in the full sample.

Table 1 here

Table 2A presents the probit estimates of the waiting time model with a cut-off point of 100 days, utilising the same supply and needs variables as identified by Smith et al. (1994) to determine utilisation. After consulting health experts at the King's Fund, we chose 100 days as the cut-off point, as we were advised that this length of waiting time is seen by health care providers as a reasonable time to go through the system. It is clear from the likelihood ratio test that the supply variables are informative for waiting times. Better access to NHS and private hospitals decreases the average waiting time for routine surgery, whereas more GP's in the area has the effect of increasing the average waiting time.

Table 2B presents four sets of results for the demand equation as specified in (2.3). The first column presents OLS results based on the full sample. The second column gives OLS results on the subsample of wards with an average waiting time smaller than 100 days. In the third column the two-step estimation results are presented, and finally in the fourth column the semi-parametric estimates using the Robinson method are presented. In the Robinson method, the kernel function is specified as the standard normal and the bandwidth is set equal to $N^{-2/5}$. For the OLS estimators, the reported standard errors are robust to general heteroscedasticity. For the two-step and semi-parametric estimators, the standard errors are estimated using bootstrap resampling methods. The estimators, including the probit, are calculated for 100 bootstrap samples, and the reported standard errors are the standard deviations of these estimates. The results of the two-step estimator indicates that the selection is indeed endogenous, as the coefficient on the correction term is significant. It is further negative, indicating that the unobservables u^d in the demand equation and the unobservables ε in the waiting times model are positively correlated which is as expected. The coefficient estimates from the two-step estimator are quite different from the OLS results based on the full sample, especially the coefficient on HSIR074 is significantly smaller. The results of the semi-parametric selection estimator are very similar to those of the two-step estimator, indicating that the normality assumption is not violated.

Tables 2A, 2B and 2C here

Table 2C gives the impact of the four different results for the allocation of resources to the regions. The first column gives the population weighted need indices for a selected clustering of wards, based on the simple OLS regression results of the demand equation using the full sample of wards. Deprived inner city areas and wards in inner London have the highest need indices, whereas rural areas have the lowest. The next columns in Table 2C give the percentage change in need indices based on the other three estimation results and show some marked differences. Using the two-step and semi-parametric estimation results, the wards in greater London have a higher needs index than before, whereas primarily the inner city and urban areas have a lower index. Note that the actual allocation formula that is currently in use is based on multilevel model estimates that take account of 186 District Health Authorities (DHA). As we believe that these district effects are correlated with the explanatory variables, they should be modelled as fixed effects dummy variables (see Blundell and Windmeijer (1997)). This is complicated for the nonlinear probit model, and we don't pursue it in this paper. The allocation results as presented here are therefore not a direct comparison with current practice.

The results presented above were based on the model specification of Smith et al. (1994) that was selected without using multilevel modelling procedures. Our results are different for various reasons. First of all we use a different dependent variable, the utilisation in 1991-92, and not the average of the years 1990-91/1991-92. Secondly we estimate the demand equation using only those wards with low waiting times, correcting for the endogenous selection. As is clear from the results as presented in Table 2B, not all demand variables have a significant impact on utilisation using our modelling approach. We therefore performed a specification search, selecting needs variables using the two-step selection method. The need variables identified in this way are very similar as before, but the variables S_CARER and UNEMP are replaced by NOCAR and MANUAL. Tables 3A, 3B and 3C present the set of results for this model. Again the sample selection term in the two-step estimator is significant with the expected sign, and the parametric and semi-parametric estimates are very similar. In comparison to the first model, however, the needs indices for London are substantially lower whereas those for the rural areas are higher.

Tables 3A, 3B and 3C here

As stated in the previous section, our modelling strategy assumes that waiting times do not affect demand when they are smaller than W^m. In Table 4 we present instrumental variables estimation results for the demand equation that includes the (log of) the waiting times linearly in the model, as specified in (2.2). The endogenous waiting times are instrumented by the four lagged supply variables. The first column presents results for the full sample, and the waiting time has a significant negative effect on demand. The second column presents the results for the selected sample including the Heckman sample selection correction. In this case, the effect of waiting time is small and insignificant, supporting our initial assumptions. The latter model is identified as there are four instrumental variables that instrument both the selection correction term and the waiting times variable.

Table 4 here

We have chosen the cut-off point of 100 days as that is seen by health care providers as a reasonable time to go through the system. When we repeat the instrumental variables regression including waiting times, but for different selected samples for different values of W^m, we find that the waiting time variable is significantly negative for values of W^m of 117 and higher, and insignificant for values of W^m lower than 117. In the light of this it appears that the cut-off point of 100 days is appropriate. However, to check robustness of the results, we present in Table 5 estimation results for a selected sample with a cut-off point of 110 days waiting. The sample size in this case is much larger. The results, however, are very similar to those as presented in Table 3B.

Table 5 here

4. Conclusions

The aim of this paper has been to recover the determinants of demand for hospital services in a framework that acknowledges the importance of supply constraints in the public sector provision of health care. Waiting times are assumed to act as a hassle cost that chokes off demand when resources are constrained. In the full equilibrium model waiting times act like a price that maintains full equilibrium. Because our interest has been in the determinants of demand we do not fully model supply but simply use the determinants of supply as instruments for waiting time in our specification of demand.

To measure the determinants of demand we chose, as our central specification, a model that selects only those areas with low waiting times. Our results are then corrected for this endogenous selection. We argue that the focus on demand at low waiting times avoids systematic measurement error at high waiting times and also avoids the specification of the interactions between needs variables at higher waiting times. In estimation we compare our specification to alternative models.

We have applied our approach to a sample of ward level data from the UK and study the demand for acute care. We contrast our model estimates, and their implications for health services resource allocations in the UK, to more standard allocation models. We find that correcting for supply constraints through the selection of low waiting time areas changes allocation formulae in important ways.

Allocation formulae that are based on models relating needs to use require the explicit modelling of the process by which use is determined. In case of the NHS, identifying needs from acute hospital care utilisation data should take into account the method of rationing by waiting times.

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Table 1: Descriptive statistics

Variable	Description	All Wards N = 4955 Mean	All Wards N = 4955 Std. Dev.	WT91<100 N = 1296 Mean	WT91<100 N = 1296 Std. Dev.
WT91	Average waiting time routine surgery in days	117.08	26.18	85.74	11.10
ACCOS91	standardised estimated costs 1991-92 acute care	100.63	23.01	102.07	23.09
ACCNHS	NHS hospital accessibility	2.34	0.75	2.34	0.76
ACCGPS	GP accessibility	0.53	0.13	0.53	0.12
HOMES*	1-proportion of 75+ in nursing and residential homes	0.94	0.06	0.95	0.05
ACCPRI	private hospital accessibility	0.17	0.13	0.18	0.18
SMR074	standardised mortality ratio - ages 0-74	99.46	23.16	101.52	23.16
HSIR074	standardised illness ratio - ages 0-74, for residents in households only	99.01	30.59	104.15	31.99
MANUAL	proportion of persons with head in manual class	0.46	0.15	0.49	0.14
OLDALONE	proportion of those of pensionable age living alone	0.33	0.06	0.33	0.05
S_CARER	proportion of dependants in single carer households	0.19	0.06	0.20	0.06
UNEMP	proportion of the economically active that is unemployed	0.09	0.05	0.10	0.05
NOCAR	proportion of residents in households with no car	0.24	0.14	0.25	0.14

Note: In the regressions, natural logarithms are taken of all variables

Table 2A: Results for Probit regression

Weighted regression Dep. Var. WT91>100	N = 4955		R2 = 0.14
Variable	B	SE B	T
ACCNHS	-0.1651	0.1027	-1.6074
ACCGPS	0.1901	0.1212	1.5687
ACCPRI	-0.2361	0.0625	-3.7784
HOMES*	-0.0130	0.3267	-0.0398
OLDALONE	0.3400	0.1784	1.9059
S_CARER	-0.2461	0.1466	-1.6784
UNEMP	0.2912	0.1070	2.7217
HSIR074	-0.3113	0.2078	-1.4979
SMR074	-0.2106	0.1730	-1.2174
LR test for supply variables : 34.51, p-value 0.0000			
Dummies included for Regional Health Authorities Observations weighted by ward population			

Table 2B: Results for needs regressions

Weighted regression
Dep. Var. ACCOS91

	OLS full sample		OLS selected sample		two-step estimator		semi-parametric estimator	
N	4955		1296		1296		1296	
R^2	0.50		0.57		0.57		0.53	
Variable	B	SE B	B	SE B	B	SE^* B	B	SE^* B
OLDALONE	0.1191	0.0190	0.1391	0.0369	0.1670	0.0426	0.1532	0.0409
S_CARER	0.0036	0.0180	0.0755	0.0393	0.0468	0.0301	0.0431	0.0306
UNEMP	0.0248	0.0114	0.0227	0.0202	0.0593	0.0391	0.0490	0.0425
HSIR074	0.2848	0.0241	0.2053	0.0399	0.1595	0.0411	0.1734	0.0449
SMR074	0.1342	0.0219	0.1135	0.0384	0.0831	0.0437	0.1097	0.0469
λ					-0.1865	0.0650		

Dummies included for Regional Health Authorities
SE^*: Standard deviation of 100 bootstrap estimates
Observations weighted by ward population

Table 2C: Population weighted need indices

Cluster Summaries	Full sample OLS	Selected sample OLS	Selected two- step	Selected semi-parametric
Inner London	112.3	1.10%	1.68%	1.28%
Mixed Status London	100.3	0.76%	1.66%	1.25%
Outer London	94.3	1.10%	2.01%	1.62%
Inner City Deprived	113.2	-0.80%	-1.30%	-1.11%
Urban Areas	107.9	-1.22%	-2.10%	-1.72%
Resort and Retirement Areas	96.0	1.07%	1.23%	0.96%
High-Status Suburban	93.5	0.62%	1.14%	0.97%
High-Status Rural	88.5	0.29%	1.29%	1.08%
High-Status Urban	98.0	-0.30%	-0.37%	-0.25%
Rural Areas	95.9	0.26%	0.09%	0.11%
Dormitory Towns	106.2	1.32%	1.55%	1.34%

Table 3A: Results for Probit regression

Weighted regression	N = 4955		R2 = 0.14
Dep. Var. WT91>100			
Variable	B	SE B	T
ACCNHS	-0.1530	0.1073	-1.4264
ACCGPS	0.1743	0.1288	1.3529
ACCPRI	-0.2325	0.0626	-3.7137
HOMES*	-0.1034	0.3370	-0.3066
OLDALONE	0.2274	0.2104	1.0810
NOCAR	0.1192	0.1055	1.1295
MANUAL	-0.0222	0.1003	-0.2210
HSIR074	-0.2377	0.2032	-1.1699
SMR074	-0.1581	0.1734	-0.9118
LR test for supply variables : 30.24, p-value 0.0000			
Dummies included for Regional Health Authorities			
Observations weighted by ward population			

Table 3B: Results for needs regressions

Weighted regression
Dep. Var. ACCOS91

	OLS full sample		OLS selected sample		two-step estimator		semi-parametric estimator	
N	4955		1296		1296		1296	
R^2	0.51		0.57		0.58		0.49	
Variable	B	SE B	B	SE B	B	SE^* B	B	SE^* B
OLDALONE	0.0916	0.0235	0.0979	0.0423	0.1258	0.0499	0.1224	0.0464
NOCAR	0.0475	0.0101	0.0629	0.0185	0.0775	0.0232	0.0630	0.0214
MANUAL	0.0371	0.0106	0.0433	0.0227	0.0565	0.0237	0.0541	0.0219
HSIR074	0.2166	0.0226	0.1722	0.0390	0.1192	0.0518	0.1482	0.0504
SMR074	0.1259	0.0216	0.1049	0.0379	0.0752	0.0456	0.0996	0.0435
λ					-0.2256	0.0621		

Dummies included for Regional Health Authorities
SE^*: Standard deviation of 100 bootstrap estimates
Observations weighted by ward population

Table 3C: Population weighted need indices, as compared to first model, Table 2C, columns 3 and 4

Cluster Summaries	Selected two- step	Selected semi-parametric
Inner London	-2.36%	-2.18%
Mixed Status London	-1.19%	-1.18%
Outer London	-0.65%	-0.79%
Inner City Deprived	-0.59%	-0.40%
Urban Areas	0.42%	0.55%
Resort and Retirement Areas	-0.11%	-0.14%
High-Status Suburban	-0.05%	-0.13%
High-Status Rural	0.69%	0.47%
High-Status Urban	0.20%	0.19%
Rural Areas	0.93%	0.82%
Dormitory Towns	-2.36%	-2.33%

Table 4: Results for IV estimator with WT91 included. Instrumented by lagged supply variables.

Weighted regression Dep. Var. ACCOS91	Full Sample N = 4955		Selected Sample N =1296	
Variable	B	SE B	B	SE* B
OLDALONE	0.2381	0.0846	0.1025	0.0701
NOCAR	0.0773	0.0356	0.0765	0.0271
MANUAL	0.0922	0.0355	0.0568	0.0282
HSIR074	-0.0017	0.0958	0.0736	0.0739
SMR074	0.1350	0.0611	0.1225	0.0758
WT91	-2.4851	0.6750	-0.7449	0.8128
λ			-0.1863	0.0921

Dummies included for Regional Health Authorities
SE*: Standard deviation of 100 bootstrap estimates
Observations weighted by ward population

Table 5: Results for needs regressions. Selected sample, WT91<110

Weighted regression Dep. Var. ACCOS91	two-step estimator		semi-parametric estimator	
N	2016		2016	
R^2	0.57		0.54	
Variable	B	SE* B	B	SE* B
OLDALONE	0.1056	0.0487	0.1094	0.0515
NOCAR	0.0868	0.0223	0.0859	0.0248
MANUAL	0.0574	0.0250	0.0616	0.0257
HSIR074	0.1296	0.0502	0.1288	0.0551
SMR074	0.0740	0.0457	0.0766	0.0484
λ	-0.3505	0.1216		

Dummies included for Regional Health Authorities
SE*: Standard deviation of 100 bootstrap estimates
Observations weighted by ward population