Waiting Lists, Waiting Times and Admissions; An Empirical Analysis at Hospital and Specialty Level[+]

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1. Introduction

This paper describes the results of an empirical analysis of the responses of inpatient, outpatient and emergency admissions to waiting list size and waiting times at the aggregate level for a hospital in a Scottish health board and for orthopaedics at two hospitals, Hospitals 1 and 2, in the same NHS board. The analysis focuses on two distinct parts. The first part is an extensive time series analysis at the hospital level to model supply responses to various measures of current and past waiting times, list sizes and activity levels. The second part focuses on the demand side by modelling the realised outpatient referral rates of the GP practices in response to outpatient waiting times. The latter part is done only for the aggregate demand at hospital 1 and not repeated at the specialty level. The two analyses are then brought together in order to perform simulations of the impact of increased activity levels on the various outcome measures over time.

The empirical models that are being estimated are based on the theoretical models of waiting lists as developed by, amongst others, Martin and Smith (1999) and Gravelle, Smith and Xavier (2000). These papers specify the theoretical background for models for demand, supply, waiting time and waiting lists that form the basis for our empirical specifications. As these models are dynamic, with past behaviour and conditions influencing future responses and outcomes, we utilize time series data at the hospital and specialty level to estimate the parameters of the various models.

For demand responses to waiting times, we utilise data at the GP practice level. As the constructed data are repeated time series observations per GP practice, these constitute a panel dataset allowing us to estimate dynamic models controlling for unobserved, fixed, GP heterogeneity in referral rates. The referral rates that are being modeled are the realised outpatient visits rates, with demand responding to changes in the mean outpatient waiting duration, controlling for demand shifters such as socio-economic and morbidity characteristics of the GP practice population and GP practice characteristics.

Most of the empirical model specifications that are found adhere quite closely to the theoretical models, with most signs of estimated coefficients in line with expectations. We can therefore meaningfully combine the various estimation results to perform a simulation. We increase the number of elective inpatient and day-case admissions exogenously by 10%, sustained for three months, and calculate the responses to the various waiting measures that subsequently feed back into activity levels. The paths of the waiting measures and activity levels is charted for 21 months after the exogenous

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increases in activity levels on the assumption that all responses remain as they were estimated from past behaviour. These give some important insights of how the system responds to various pressures, and how long it takes for it to be back at its original path. For example, for the aggregate supply and demand at Hospital 1 we find that the system is back to its original levels at the end of the simulation period, 21 months after the three months sustained 10% increases.

The structure of the paper is as follows. Section 2 introduces the theoretical models of demand, supply, waiting time and waiting lists as derived by Gravelle, Smith and Xavier (2000) and presents a description of the data and data sources. Section 3 presents the time series analysis of the models for supply, waiting times and waiting lists for the aggregate series at Hospital 1. Section 4 reports on the panel data analysis of the model for demand, the realised GP outpatient visits rates at the specific hospital. These estimation results are combined in a simulation exercise as described above in Section 5. Section 6 repeats the time series analysis for the specialty orthopaedics at the two hospitals in the health board and the results of the simulation exercise for both hospitals. Section 7 concludes.

2. Models and Data

The empirical models that are utilized in this study follow the theoretical models of waiting lists as developed by, amongst others, Martin and Smith (1999) and Gravelle, Smith and Xavier (2000). In the following we draw heavily from Gravelle, Smith and Xavier (2000), henceforth GSX.

GSX start by specifying a model for the demand for elective care at time t, D_t, following the specification as developed by Lindsay and Feigenbaum (1984). First of all, patients in need of care for a non-life threatening condition visit their general practitioner to decide whether to seek hospital care. Then the patient must first been seen in the outpatient department by the hospital doctor who decides whether to place the patient on the waiting list for elective care. The benefit of treatment to the patient is diminishing with increased waiting time. The GSX model for demand for elective care is given by the relationship

$$D_t = D\left(w_t^p, z_t^d\right),$$

where w_t^p is the waiting time perceived by patients when considering joining the waiting list in period t and z_t^d comprises demand shifters such as socio-economic and morbidity characteristics of the population. The perception of expected waiting time for patients added to the list in period t might be the time to clear last period's list, $w_t^p = L_{t-1} / S_{t-1}$. In the model for hospital admissions, GSX assume that decisions are taken by a hospital manager with period t utility function

$$u_t = u\left(S_t, L_t, w_t^m; z^s\right),$$

where S_t is the number of patients admitted, L_t is the number of people on the waiting list at the end of the period, w_t^m is the manager's perception of the waiting times or list performance measure and z^s are exogenous factors affecting the manager's utility. The waiting list is assumed to evolve as

$$L_t = L_{t-1} + D_t - S_t,$$

where D_t is demand, the number of additions to the waiting list, where the possibility is ignored that patients leave the waiting list because of changing their minds about treatment, die or leave the area. GSX argue that supply S_t may enter the manager's

utility function because of its impact on implicit profits, or that the manager may have to work harder to increase elective throughput.
A model for the perceived waiting measure w_t^m is given by

$$w_t^m = f\left(S_t; w_{t-1}^m, L_{t-1}, D_t\right),$$

with the expectation that w_t^m decreases in current supply, and increases in last period's waiting indicator, last period's list and the number of patients added to the list in the current period. GSX argue that one specification could be that the manager cares about the time to clear the list at the end of the period, $w_t^m = L_t / S_t = \left(L_{t-1} + D_t - S_t\right)/ S_t$. By taking into account the multi-period nature of the manager's decision making process, GSX derive the optimal supply in period *t* as

$$S_t^* = S\left(L_{t-1}, w_{t-1}^m, D_t, z^s, \delta_t\right) = S^*\left(L_{t-1}, w_{t-1}^m, w_t^p, z^s, z^d, \delta_t\right)$$

where $S^*(.)$ is the reduced form supply equation and δ_t is the manager's one-period ahead discount factor.

In our empirical analysis we first estimate the models described above using time series data at hospital/specialty level for the supply and waiting list/times models. From a variety of data sources we have constructed monthly information on the number of elective inpatient admissions, the number of elective day cases, the number of emergency admissions, average length of stay, and the number of outpatient visits. Further, we constructed monthly information on realized inpatient, day case and outpatient waiting durations, and have quarterly census type information on waiting list sizes and waiting times for those on the waiting lists. We have transformed the latter quarterly information into monthly data by linear interpolation when estimating the empirical models. Table 1 provides the acronyms and definition of the variables used in the empirical analysis of the supply and waiting list/times models.
The monthly number of elective inpatient admissions (*IA*), elective day-case admission (*DA*) and emergency inpatient admissions (*EMIA*) are taken from the Scottish Health Data general acute inpatient/day-case record SMR01 dataset, which collects patient based data on inpatient and day-case episodes in general and acute wards. The length of stay for each episode is also recorded in this dataset, and the average length of stay (*LOSM*) is calculated as the average length of stay of all elective and emergency inpatient episodes during a calendar month.
The number of monthly first outpatient visits (*OV*) is taken from the outpatient record dataset SMR00. This dataset collects patient based data on first attendance at outpatient clinics in all specialties (except A&E).
The number of patients waiting for elective inpatient treatment (*WLI*) or day-case treatment (*WLD*) are taken from census data that record the number of patients waiting at a given point in time at regular intervals, in general the end of a quarter. These data have been transformed into monthly observations by means of linear interpolation when estimating the various empirical models. The census data also provide information on the length of time patients have been waiting that are on the list at the time of the census. From this we have calculated the mean waiting time for those patients waiting for inpatient treatment (*WTIM*) and the median waiting time (*WTI5*), and the mean and median waiting times for those patients waiting for day-case treatment (*WTDM* and *WTD5* respectively). These quarterly observations on waiting times have also been transformed to monthly observations by linear interpolation when estimating the empirical models.

Table 1. Variable acronyms and descriptions		
Acronym	Description	Data source
IA	Inpatient elective Admissions	SMR01
DA	Day-case elective Admissions	SMR01
EMIA	EMergency Inpatient Admissions	SMR01
OV	First Outpatient Visits	SMR00
WLI	Waiting List Inpatient elective[1]	Census
WLD	Waiting List Day-case elective	Census
WTIM/5	Waiting Time Inpatient elective Mean/Median, days	Census
WDIM/5	Waiting Duration Inpatient elective Mean/Med, days	SMR00
WTTCI	Time to clear list, inpatient elective	Derived
WTDM/5	Waiting Time Day-case Elective Mean/Med, days	Census
WDDM/5	Waiting Duration Day-case elective Mean/Med, days	SMR01
WTTCD	Time to clear list, day-case elective	Derived
WDOM/5	Waiting Duration Outpatient Mean/Med, days	SMR00
LOSM	inpatient Length Of Stay Mean, days	SMR01
NBeds	Number of Beds	Hosp_beds
FBBeds	Fraction of “blocked” beds[2]	

We have further constructed different waiting times variables. The SMR01 records for most patients how long they have been on the inpatient or day-case waiting list before being admitted. These are therefore the *realised* waiting durations from the time of being put on the waiting list, in contrast to the census waiting times that refer to the stock of patient waiting at that point in time. We refer to the realised durations as durations in order to distinguish them from the census waiting times. As these durations are taken from the SMR01 record dataset, the averages (*WDIM* and *WDDM* for inpatient and day-case respectively) and medians (*WDI5* and *WDD5*) are calculated from the monthly admissions. Combining the census waiting list information and the data on the number of admissions we have constructed the *waiting times to clear the list* for inpatient and day-case treatments as $WTTCI_t = WLT_t / IA_t$ and $WTTCD_t = WLD_t / DA_t$ respectively.

The outpatient record dataset SMR00 contains information for most patients on how long they have been waiting from making their initial appointment to their first outpatient visit. From these data we have constructed the mean and median outpatient waiting durations (*WDOM* and *WDO5*), again on the basis of the observed monthly number of outpatient visits.

In the next section we will first present results for the time series analysis for the supply models for Hospital 1, using the data as described above. In Section 4 we will estimate models for demand at the GP practice level for realised first outpatient visits. We describe the GP level data and models used in detail in Section 4.

[1] We use the “true” waits.

[2] Occupied by a single patient for a length of time longer than Health Resource Group trimpoints in the LOS distribution. The Health Resource Group is a case-mix measure which attempts to group together episodes of care which are of similar complexity.

3. Time Series Analysis for Hospital 1

The first part of the research focuses on a detailed analysis of the aggregate time series properties of elective admissions, emergency admissions, waiting lists and waiting times in one of the main hospitals in the Scottish NHS Health Board. Table 2 gives some summary statistics for the aggregate series for this hospital.

Our starting point for the empirical model specifications are the theoretical models as described in Section 2. For the number of admissions these suggest, for example, specifications of the form

$$IA_t = S^*\left(WLI_{t-j}, \{WTIM_{t-k}, WDIM_{t-l}, WTTCI_{t-m}\}, z^s, z^d, \delta_t\right)$$

for inpatient admissions and

$$WTIM_t = f\left(IA_t; WTIM_{t-1}, WLI_{t-1}, D_t\right),$$

for mean inpatient waiting time. Although the specification for the waiting list size is an accounting identity in Section 2, we estimate separate models for the waiting list size, as we don't observe the number of additions to the list, D_t, and because of the fact that the accounting identity for list size does not take into account that people can leave the list because they no longer seek (NHS) care or have moved to a different region.[3] An obvious starting point for a model for waiting list size is

$$WLI_t = g\left(WLI_{t-1}, IA_t, OV_{t-j}\right).$$

In all models, we allow for flexibility of the lag length with which explanatory variables enter the equation and we further allow for all activity rates, waiting list/times, length of stay and bed availability variables to enter all models. For example, it is likely that an exogenous increase in emergency inpatient admissions will lead to a decrease in elective inpatient admissions. There could also be substitution between day-case and inpatient elective admissions.

All models are estimated by OLS where it was found that transformation into natural logarithms of all variables resulted in the best model specification with respect to standard specification tests like the RESET test. This means that all estimated coefficients can be interpreted as elasticities. The variables to be included in the model were selected using a forward selection procedure. A full set of year and month indicators were originally included in the model to guard against spurious time series correlations of the various variables and to allow for exogenous shifts in preferences. The number of year and month indicators were then reduced in a final step by removing insignificant year/month effects in order to increase the number of degrees of freedom in the models and hence the efficiency of the estimated coefficients on the other explanatory variables in general.

Table 3 presents the resulting model specifications and the values of the estimated coefficients. The estimation results for elective inpatient admissions (*IA*) show that the variables that enter the model are the number of day-case admissions in the previous month, the number of emergency admissions in the current month, the number of first outpatient visits three months ago, the inpatient waiting list two months ago and the inpatient waiting time 4 months ago. The estimation results can be interpreted as follows: Outpatients visits three months ago increase inpatient admissions in the current month, with an estimated elasticity of 0.25, meaning that a 10% increase in outpatient visits three months ago increases inpatient admissions by 2.5%. An increase in the number of patients on the waiting list for inpatient elective

[3] The fact that we don't observe the number of additions to the list D_t is also a problem in the model for waiting times.

treatment two months ago leads to an increase in activity in the current month. This is clearly a supply response to waiting list changes, with an estimated elasticity of 0.48. There is also a supply response to increased inpatient elective waiting times four months ago, with an elasticity of 0.39. An increase in the number of day cases in the previous month is associated with a decrease in the number of elective inpatient admissions with an estimated elasticity of -0.45. This is a reflection of the increased substitution of elective inpatient care for elective day care and does not necessarily indicate a supply response caused by increased day case admissions. Finally, an increase in the number of emergency admissions in the current month decreases the number of elective inpatient admissions with the elasticity estimated as -0.43. All these results are very much in line with what would be expected from the theoretical models discussed above.

Table 2. Summary statistics, Hospital 1

	Mean	St. dev.	min	max
IA	693.99	113.06	417	950
DA	1012.10	136.86	777	1308
EMIA	1707.59	142.63	1402	2036
OV	3424.28	338.82	2566	4030
WLI	1486.85	148.01	1219	1780
WLD	1010.85	255.09	472	1485
WTIM	90.27	18.75	64.06	120.75
WTI5	66.35	15.08	42	94
WDIM	75.99	11.27	43.18	105.08
WDI5	39.59	7.22	20	55.5
WTTCI	66.57	9.31	53.14	89.74
WTDM	50.05	9.32	35.69	69.66
WTD5	36.48	9.08	17	51
WDDM	53.97	10.64	31.68	72.09
WDD5	38.04	14.09	13	63
WTTCD	31.28	7.63	14.62	47.94
WDOM	46.81	7.38	36.11	68.01
WDO5	31.23	4.71	21	43
LOSM	4.19	0.29	3.62	4.90
NBeds	194.60	11.22	170	213
FBBeds	0.0723	0.0050	0.0651	0.0806

The other variables in the model are some year and month effects, plus an indicator for an outlying observation in January 2000. This model passes the RESET test for misspecification. The Durbin-Watson (DW) test further indicates that there is no serial correlation problem in the residuals. The high R2 indicates a high correlation between the actual and fitted values of the number of inpatient admissions.

Table 3 shows that for elective day-case admissions (*DA*) the variables that enter the model are the number of elective inpatient admissions 2 months ago, the number of first outpatient visits 3 months ago, the median inpatient waiting time 4 months ago and the mean day-case waiting time 2 months ago. A 10% increase in average day-case waiting times two months ago leads to an increase in day-case activity of 1.7%. A 10% increase in the inpatient median waiting time four months ago is associated with an increase in the number of day-case admissions of 2.8%. The elasticity with respect to outpatient visits is 0.32, with a three months lag. Again, there is evidence of substitution between inpatient and day-case admissions, an increase in inpatient admissions two months ago is associated by a decrease in the number of day-case admissions.

The variables that enter the model for the number of emergency inpatient admissions (*EMIA*) are the inpatient waiting list in the previous month and the median realised waiting duration in the previous month. An increased number of patients on the elective inpatient waiting list in the previous month decreases the number of emergency admissions with an elasticity of –0.12. An increase in the realised elective inpatient median waiting durations in the previous month leads to an increase in the number of emergency admissions, the estimated elasticity being 0.04.

The variables that enter the model for first outpatient visits (*OV*) are the number of inpatient admissions 2 months ago, the number of first outpatient visits, one, two and three months ago, and the median realised outpatient waiting duration two months ago. There is strong serial correlation in the number of outpatient visits with an apparent three months cycle. An increased number of outpatient visits three month ago is associated with an increase in the current period, whereas increases in the last and one-before-last months are associated with a decrease in the number of outpatient visits in the current month. There is a supply response to outpatient median realised waiting durations. A 10% increase in these waiting durations two months ago increases the number of outpatient visits this month by 1.3%. An increase in the number of inpatient admissions 2 months ago is associated with a decrease in the number of outpatient visits with an estimated elasticity of –0.16.

The model for elective inpatient waiting list (*WLI*) at Hospital 1 includes the expected one-month lagged waiting list, the one month lagged number of elective inpatient admissions and the one-month lagged number of first outpatient visits. It also includes the number of day-case admissions two months ago. The short term effect of a 10% increase in elective inpatient admissions in the previous month is a decreases in the list size of 1.9%. A 10% increase in the number of day-case admissions two months ago is associated with a 1% decrease in the elective inpatient waiting list, again indicating a substitution effect. A 10% increase in outpatient visits in the previous period increases the list size by an estimated 1.2%. The coefficient on the lagged waiting list is 0.79, indicating quite strong serial correlation of the series over time.[4]

As Table 3 shows, the model for the day-case waiting list (*WLD*) at Hospital 1 includes the lagged day-case waiting list as expected. Two lags of the waiting list are incorporated in this model. Further, the number of outpatient visits in the previous month enters the model. The waiting list increases with the number of outpatient visits in the previous month, with an estimated elasticity of 0.36. Unexpectedly, the number of day-case admissions does not enter the empirical model for the day-case waiting list.

[4] The model for waiting lists as described in Section 2 is in the levels of the number of patients on the list and admitted and not in logs. Estimation of a model where the variables are not transformed into logs results in the same model specification.

Table 3. Estimation results for time series analysis, hospital level

IA		DA		EMIA		OV		WLI	
DA_1	-0.4505 (0.0757)	IA_2	-0.1702 (0.0699)	WLI_1	-0.1190 (0.0458)	IA_2	-0.1586 (0.0733)	IA_1	-0.1870 (0.0411)
EMIA	-0.4259 (0.1774)	OV_3	0.3184 (0.1104)	WDI5_1	0.0414 (0.0189)	OV_1	-0.4282 (0.0950)	DA_2	-0.1152 (0.0372)
OV_3	0.2529 (0.0877)	WTI5_4	0.2793 (0.0513)			OV_2	-0.1877 (0.1124)	OV_1	0.1243 (0.0653)
WLI_2	0.4788 (0.1243)	WTDM_2	0.1657 (0.0583)			OV_3	0.3369 (0.0890)	WLI_1	0.7943 (0.0555)
WTIM_4	0.3865 (0.1082)					WDO5_2	0.1257 (0.0538)		
# obs	60	60		66		57		59	
R^2	0.93	0.85		0.92		0.84		0.89	
RESET p	0.30	0.31		0.49		0.14		0.61	
Ser. Cor. p/DW	1.81	2.16		2.47		0.37		0.56	

WLD		WTIM		WDI5		WTDM		WDO5	
OV_1	0.3603 (0.1327)	IA	-0.1130 (0.0386)	WLI_2	0.6107 (0.2040)	DA_1	-0.1188 (0.0656)	EMIA_1	0.6280 (0.1865)
WLD_1	1.2494 (0.0960)	WLI_1	0.2310 (0.0692)			WLI_1	0.2680 (0.0897)	WLI_3	0.2610 (0.1076)
WLD_2	-0.4405 (0.0969)	WTIM_1	0.6076 (0.0779)			WLD_1	0.1809 (0.0306)	WTDM_1	0.2076 (0.0643)
						WTDM_1	0.7870 (0.0564)	WDO5_1	0.2811 (0.0682)
# obs	60	66		68		66		59	
R^2	0.88	0.97		0.59		0.91		0.92	
RESET p	0.04	0.95		0.88		0.17		0.98	
Ser. Cor. p/DW	0.45	0.15		1.70		0.09		0.73	

Note to Table 3: All variables are measured in natural logarithms, standard errors in brackets.

The variables that enter the model for mean inpatient waiting times (*WTIM*) are the number of inpatient admissions in the current month, the one month lagged inpatient waiting list and one month lagged mean inpatient waiting time, again as expected from the model specification as presented in Section 2. An increase in the number of patients on the waiting list in the previous month is associated with an increase in the average waiting time, with an estimated elasticity of 0.23. A 10% increase in the number of inpatient admissions decreases the waiting time by an estimated 1.1%. The coefficient on the lagged mean waiting time is 0.61.

The median elective inpatient realised waiting duration (*WDI5*) is affected by an increase in the number of patients on the elective inpatient waiting list. A 10% increase in the waiting list size two months ago increases the realised waiting durations by an estimated 6.1%.

The model for mean day-case waiting time (*WTDM*) is again very much in accordance with the theoretical model of Section 2. The variables that enter the model are the number of day-case admissions in the previous month, the inpatient and day-case waiting lists in the previous month and the one-month lagged mean day-case waiting time itself. The day-case waiting time increases with increased previous month's inpatient elective waiting list and day-case waiting list, with elasticities of 0.27 and 0.18 respectively. A 10% increase in day-case admissions in the previous month decreases the mean waiting time by 1.2% in the short run. The coefficient on the lagged mean day-case waiting time is 0.79, again indicating quite a strong serial correlation.

As Table 3 shows, the median outpatient realised waiting duration (*WDO5*) is affected by the number of inpatient emergency admissions in the previous month, the inpatient waiting list 3 months ago, the mean day-case waiting time in the previous month and the one month lagged median outpatient realised waiting duration. A 10% increase in the number of emergency admissions in the previous month increases the outpatient waiting durations by 6.3%. An increase in the elective inpatient waiting list 3 months ago increases the median waiting duration with an estimated elasticity of 0.26. An increase in the day-case waiting time in the previous month increases the median outpatient waiting duration, the estimated elasticity being 0.28. The coefficient on the lagged median outpatient waiting duration is 0.28, so the serial correlation is not strong.

4. GP Practice Outpatient Visits Rates – A Panel Data Analysis

The second part of the research is an analysis of the number of realised outpatient visits at Hospital 1 per GP practice in the health board area. This is done in order to proxy the demand side of health care as GP's have the role of gatekeepers. The aim of this modelling exercise is to establish a demand response to waiting lists and/or waiting times at the hospital. We have available a panel of 65 GP practices with at most 19 quarterly observations, for the period 1997q2-2001q4.[5]

As outlined in Section 2, the GSX model for demand for elective care is given by the relationship

$$D_t = D\left(w_t^p, z_t^d\right)$$

where w_t^p is the waiting time perceived by patients when considering joining the waiting list in period *t* and z_t^d comprises demand shifters such as socio-economic and

[5] Using monthly data would result in too many zero outpatient visits.

morbidity characteristics of the population. The empirical model that we estimate for the realised outpatient first visit rate by GP practice is of this form and given by

$$OVR_{it} = \alpha WDOM_{t-s} + \sum_{j=1}^{J} \beta_j x_{itj} + \sum_{l=1}^{L} \gamma_l z_{il} + u_{it}$$

where the index *i* denotes a GP practice and *t* denotes a time period, *OVR* is the realised outpatient visit rate per practice and *WDOM* is the mean realised waiting duration for first outpatient visits at the hospital. The x_{it} contain "need" variables that include the age/sex profile of the GP patient population, the fraction of deaths of patients aged 0-64 at the practice level, and the standardised illness ratio, which is the all age/sex standardised proportion with a limiting long-term illness using 1991 figures for the area where the GP practice is located.[6] The z_i contain variables that are GP practice characteristics and include the distances to the hospital and the alternative Hospital 2, whether the practice is located on an island, whether the practice can dispense pharmaceuticals, whether he practice can perform minor surgery and the number of partners. We further include year and quarter indicators in the model.

Table 4 presents a description of the variables used and their acronyms, together with some summary statistics. On average, just over 2% of GP patients have a first outpatient visit per quarter.

Table 4. Variable description and summary statistics of pooled data

Variables	Description	Mean	St. Dev.
OVR	Outpatient visits rate	.0228	.0173
FRAGE01	Fraction of GP patients between 0 an 1 years of age (x100)	1.8974	.4161
FRAGE24	2-4	3.2802	.6778
FRAGE514	5-14	12.5393	1.8933
FRAGE1519	15-19	6.2160	.8439
FRAGE2024	20-24	5.4411	.8963
FRAGE2544	25-44	28.6507	2.9269
FRAGE4564	45-64	25.1598	2.4548
FRAGE6574	65-74	9.3303	2.2763
FRAGE7584	75-84	5.6095	1.6348
FRAGE85P	85+	1.8752	.8285
FRFEMALE	Fraction of GP patients female	51.0354	2.2568
DIST_HOSP1	Distance from GP practice to Hospital 1 (km)	19.1182	12.5393
DIST_HOSP2	Distance from GP practice to Hospital 2 (km)	20.8467	11.9634
D_ISLAND	Indicator for GP practice on island	.0672	.2505
D_DISPEN	Indicator for dispensing GP practice	.0504	.2189
D_MINORS	Indicator for GP practice performing minor surgery	.7212	.4485
PARTNERS	Number of partners	4.0639	2.0897
SIR91	Standardised Illness Ratio 1991	104.3237	25.0756
FRDEATHS_064	Fraction of deaths, ages 0-64 * 100	.0682	.0476
DFRD_064	Zero deaths ages 0-64	.1154	.3197

[6] These variables were selected from various "need" indicators, including Arbuthnott indices, using standard model selection procedures.

Table 5. OLS results for GP level log outpatient visits rate, Hospital 1

Variables	Coeff	Se	t-ratio
Dep. Var. *LOVR*			
LWDOM_2	-.3325	.1821	-1.83
FRAGE01	-.0066	.1720	-0.04
FRAGE24	-.1473	.1347	-1.09
FRAGE514	-.1575	.0809	-1.95
FRAGE1519	-.0249	.1084	-0.23
FRAGE2024	.1568	.1339	1.17
FRAGE2544	-.0453	.0531	-0.85
FRAGE4564	-	-	-
FRAGE6574	-.0466	.1107	-0.42
FRAGE7584	-.2407	.1067	-2.25
FRAGE85P	-.0976	.1731	-0.56
FRFEMALE	.0574	.0274	2.09
LDIST_HOSP1	-.6983	.1089	-6.41
LDIST_HOSP2	.5488	.0933	5.88
D_ISLAND	1.3438	.3611	3.72
D_DISPEN	-1.1861	.2614	-4.54
D_MINORS	.1824	.1706	1.07
LPARTNERS	-.1735	.1245	-1.39
LSIR91	.8426	.3089	2.73
LFRDEATHS_064	.0591	.0294	2.01
DFRD_064=0	.0293	.0816	0.36
Y1997	-.1241	.0643	-1.93
Y1998	-.0355	.0373	-0.95
Y1999	-	-	-
Y2000	-.0184	.0286	-0.64
Y2001	.0692	.0500	1.39
Q1	-.0216	.0129	-1.67
Q2	-	-	-
Q3	-.0184	.0159	-1.16
Q4	-.0120	.0172	-0.70
#OBS	997		
#GP practices	61		
Time period	1997q4-2001q4		
R2	0.75		
RESET	189, p-value 0.00		
Notes: The prefix *L* indicates a logarithmic transformation of the variable.			
Standard errors are robust to heteroskedasticity and general correlation over time			
of the residuals by GP practice			

Table 5 presents estimation results for the GP-practice level data. These results are from a simple OLS regression (weighted by the number of patients per GP practice) on the pooled data. We find a negative response of the outpatient visits rate with respect to the mean waiting duration for outpatient visits at the hospital. A 10% increase in the mean waiting duration 2 quarters ago leads to a decrease of 3.3% in the GP level outpatient visits rate. There is no very clear age pattern discernable. With the fraction of the GP patient population aged 45-64 as reference point, the fractions aged 5-14 and 75-84 are associated with less outpatient visits. A higher fraction of females is associated with more outpatient visits. GP practices closer to the hospital and further away from the alternative hospital have higher outpatient visits rates. Island GP practices have higher outpatient visits rates, whereas dispensing GP practices have less.[7] Both the local need indicators, the standardised all-ages limiting long term sickness ratio in 1991, and the fraction of deaths in the GP patient population aged 0-64 are found to have an expected positive effect on the outpatient visit rate.

As the mean outpatient waiting duration at Hospital 1 is not correlated with the GP practice level characteristics, dropping these characteristics from the model does not alter the waiting duration elasticity much. Estimation of a model that excludes all variables except the outpatient waiting duration and time indicators results in an estimated elasticity of –0.3047 with a standard error of 0.1692. When we include GP practice specific constants, also known as "fixed effects", the waiting duration elasticity estimate is –0.0920 with a standard error of 0.2322, clearly adding all the GP specific constants reduces the information to estimate the waiting duration elasticity precisely.

It is interesting to assess the habit persistence of GP's. This could be modelled as GP fixed effects, i.e. some GP's always have higher outpatient visits rates than others, or as a dynamic process, a high outpatient visit rate in the past leads to a higher outpatient visit rate in the present (see also Goddard and Tavakoli (1998)). A combination of these two processes is of course very likely to be the appropriate model. Table 6 present OLS results of a dynamic model in the first column. The coefficient on the lagged outpatient visits rate is very high, almost 1, indicating that the GP outpatient visits rates are very persistent indeed. This could be due to a mixture of habit persistence and unobserved GP practice characteristics. The results in the second column in Table 6 are the estimates from a dynamic panel data model estimated by the Generalised Method of Moments (GMM) using the so-called "system" moment conditions (see Blundell and Bond (1998)), that are valid under certain circumstances in dynamic models with unobserved GP heterogeneity. The coefficient on the lagged outpatient visits rate is now 0.67. In both models, the (short-term) outpatient waiting duration elasticity is estimated as –0.42.

5. Combining the Results, a Simulation Exercise

In this section we present some simulation results when combing the time series supply and the GP practice level demand results. Figure 1 below charts the relationships and feedbacks between the various activity and waiting list/times variables found in the empirical analysis, including the GP outpatient visit rate response to outpatient waiting durations.

As all estimated coefficients are elasticities, we can set some exogenous changes in percentage levels, and calculate the results in terms of changed waiting lists/times and activity levels, also in percentages, for the months following the exogenous changes.

[7] 50% of island practices are also dispensing practices.

Table 6. OLS and GMM results for GP level log outpatient visits rate, dynamic model				
	OLS		GMM System	
Variables	Coeff	Se	Coeff	Se
Dep. Var. *LOVR*				
LOVR_1	.9822	.0042	.6696	.0698
LWDOM_2	-.4265	.2058	-.4232	.2425
Y1997	-.0247	.0277	-.0214	.0393
Y1998	-.0178	.0196	-.0276	.0256
Y2000	.0158	.0110	-.0034	.0182
Y2001	.0929	.0345	.1009	.0428
Q2	.0483	.0208	.0156	.0229
Q3	.0230	.0206	.0162	.0208
Q4	.0227	.0226	-.0142	.0272
#OBS	1034		1034	
#GP practices	65		65	
Time period	1997q4-2001q4		1997q4-2001q4	
R2	0.95		Sargan p, 0.49	
RESET	12.20, 0.00		P-Ar1, 0.00, P-Ar2, 0.46	
Notes: GMM estimation results obtained with the Stata routine XTABOND2				
Reported are two-step results with Windmeijer (2004) corrected standard errors.				
Instruments used are *LOVR_2..LOVR_4*				

We simulate the effects of a 3 months sustained 10% increase in both inpatient elective admissions and day-case admissions. During this period the direct feedbacks between elective inpatients admissions, day-case admissions and outpatient visits are set to zero, but they are allowed to develop in the months after. The GP outpatient visits rate elasticity with respect to outpatient waiting durations has been set equal to –0.4, with a four-month lag. Figure 2 presents the monthly percentage changes in the various activity and waiting list/times series in the months after the initial 3 months of increased activity. The way to interpret these is that if for example the elective inpatient admissions are –2%, this means that activity levels are 2% below what they would otherwise have been.

The results can be summarized as follows. The increased activity levels lead to a decrease in inpatient waiting list and inpatient, day-case and outpatient waiting times for the first 9-14 months. For the waiting durations, the largest relative effect is found for the mean day-case waiting time, which is almost 6% lower 3 months after the sustained increases in activity levels. The inpatient waiting list is about 6.5% lower than it would have been one month after the sustained increases. Because the model for day-case waiting lists does not contain the day-case activity levels, there is no decrease in the day-case waiting list. We will return to this issue below. Due to the decreased pressure on the system, there is a decrease in the number of inpatient and day-case admission for the first 8-11 months after the 3 months sustained 10% increase in inpatient and day-case admissions. Especially the number of elective inpatient admissions is almost 4% lower in months 6 and 7, whereas the number of day-case admissions decreases by around 1% in the months 7-10. After this period, waiting lists and times start to become higher than they otherwise would have been, and inpatient and day-case activity have a positive response to this. There is a slight increase in the number of outpatient visits, peaking in month 12 at 1%, and there is a

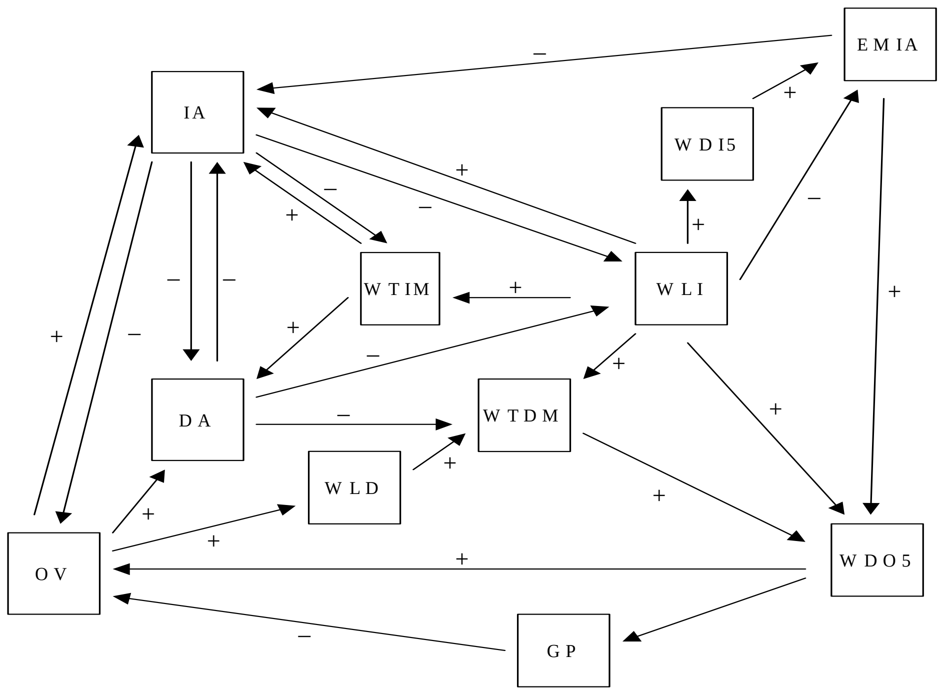

Figure 1. Flowchart of relationships found in the empirical models for Hospital 1.

slight initial increase in the number of emergency admissions. After about two years the system is almost back to its original levels.
In Figure 3, we impose an elasticity of the day-case waiting list size with respect to the number of day-case admissions equal to that of the inpatient elasticity, -0.1870. There now is of course a clear initial reduction in the day-case waiting list size, but this does not affect the results for the activity levels by much, as the day-case waiting list enters the model for activity levels only indirectly via the day-case waiting times.

6. Orthopaedics

We have repeated the full time series analysis for the specialty orthopaedics at the two hospitals in the area. Table 7 gives some summary statistics for some series at both hospitals.

Table 7. Descriptive Statistics, Orthopaedics				
	Hospital 1		Hospital 2	
	Mean	Std Dev	Mean	Std Dev
IA	100.28	22.17	51.21	10.22
DA	49.01	14.25	52.27	9.23
EMIA	135.31	18.69	101.96	14.62
OV	343.83	47.22	339.15	46.24
WLI	470.19	153.56	159.15	23.16
WLD	151.69	37.64	110.65	26.33

Tables 8 and 9 contain the selected model specifications and report the estimated coefficients for the models for orthopaedics at Hospitals 1 and 2 respectively.
Figures 4 and 5 show the results of the same simulation exercise as was done for Hospital 1 as a whole, namely a 10% increase in elective inpatient and day-case orthopaedics admissions sustained for three months at both hospitals, for orthopaedics

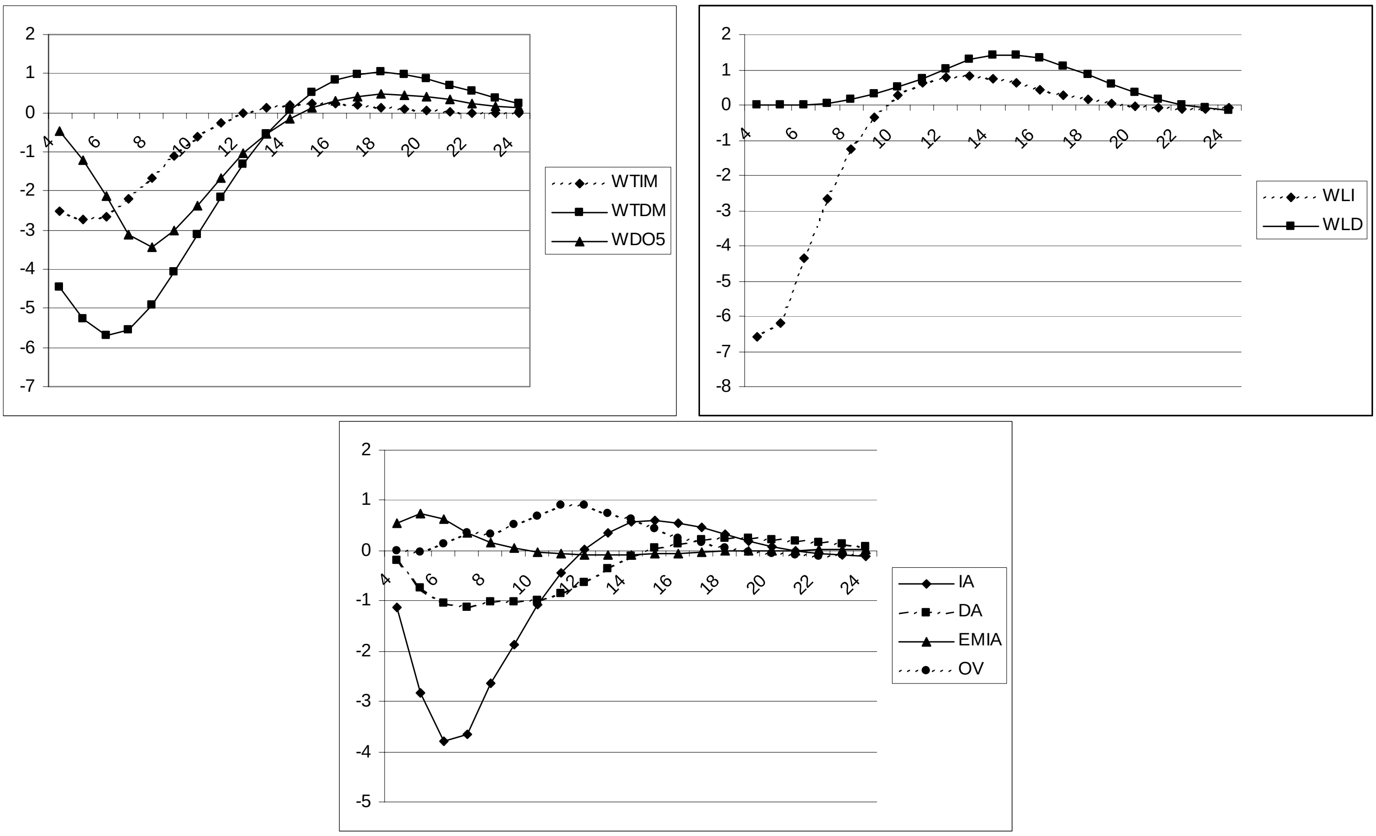

Figure 2. Effects on activity and waiting lists/times after an exogenous 3 months 10% increase in elective inpatient and day-case admissions.

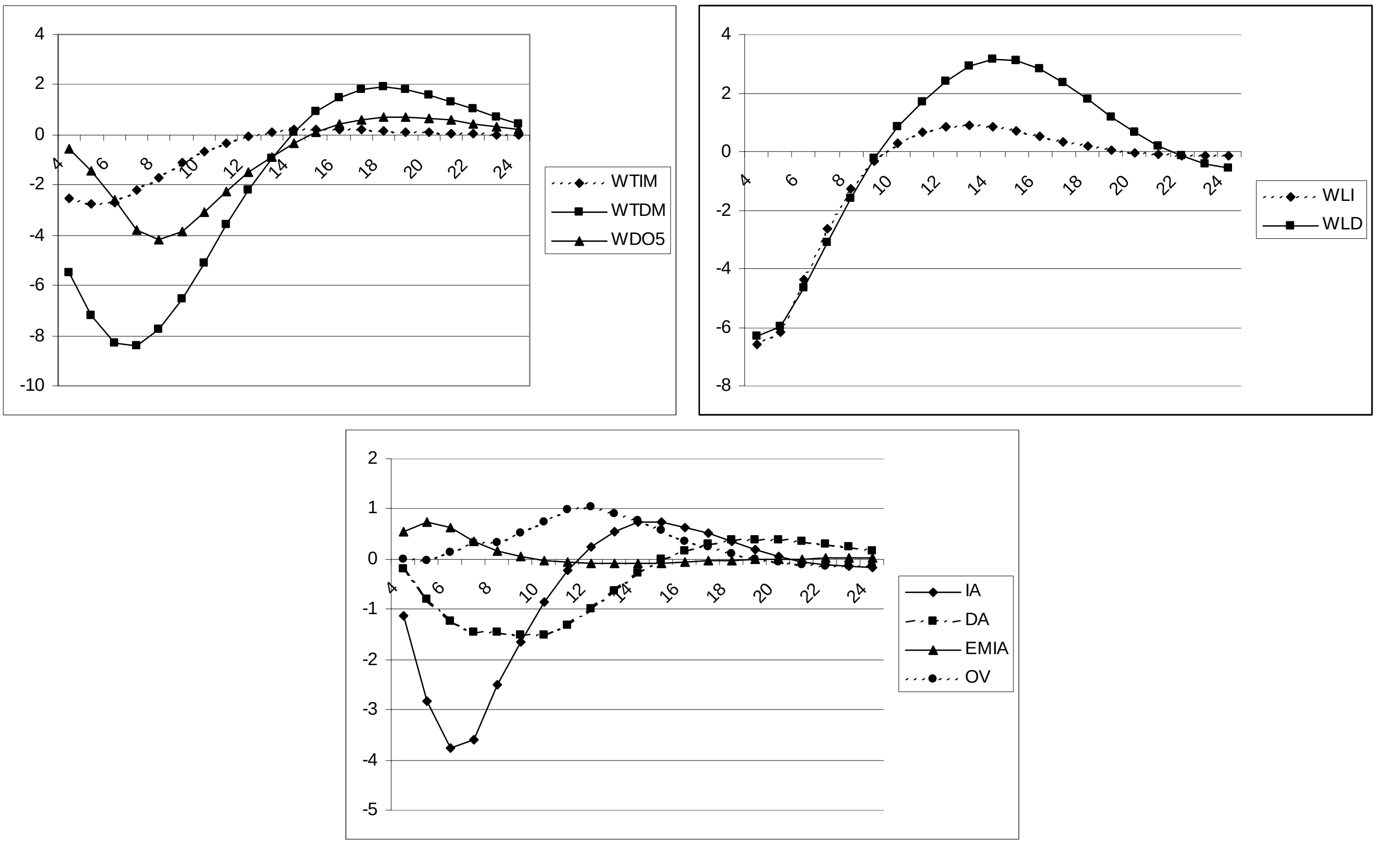

Figure 3. Effects on activity and waiting lists/times after an exogenous 3 months 10% increase in inpatient and day-case admissions, imposing elasticity of day-case waiting lists w.r.t. day-case admissions as for inpatient waiting lists and admissions.

at Hospitals 1 and 2 respectively. The figures show the responses in the 21 months after these increases on the basis of the estimation results as reported in Tables 8 and 9. We have not estimated a separate model for GP "demand", the realised outpatient referral rates for orthopaedics, but we have used the same elasticity of –0.4 with respect to outpatient waiting duration four months ago.

Figure 4 shows that there are substantial falls in the waiting times and waiting lists for orthopaedics at Hospital 1, the differences with what it would have been remaining negative for the full two-year period. The mean inpatient waiting time is 3.5% lower than what it would have been in month 4, with the difference steadily getting smaller thereafter. The median day-case waiting time is 5.2% lower in the first month after the sustained increases in activity levels, this difference quickly becoming –1.8% in month 6 and then also steadily becoming smaller. The mean outpatient waiting duration is 1.5% smaller than it otherwise would have been in month 4, this gap widening to –2.7% in month 9 after which the gap also steadily becomes smaller.

The inpatient waiting list and day-case waiting lists are 3.1% and 4.3% lower than they otherwise would have been respectively in month 4. These differences become steadily smaller after that for both waiting lists.

Figure 5 shows the simulated effects for orthopaedics at Hospital 2. Whereas at Hospital 1 the inpatient and day-case waiting times *WTIM* and *WTD5* were found to be important drivers for supply responses, at Hospital 2 the realised inpatient and day-case waiting durations *WDIM* and *WDDM* play this role. As can be seen, the mean inpatient waiting duration is 1% smaller in month 4 and 3.6% smaller than it otherwise would have been in month 7, after which the gap decreases steadily, still remaining –0.5% at the end of the two-year period. The mean day-case waiting duration is 1.6% smaller in month 4 and 4.5% smaller in month 6. The gap then decreases quickly again to –1.7% in month 9, after which it steadily gets smaller, reaching –0.15% at the end of the period. There is no difference to the mean outpatient waiting time in month 4, but the gap increases to –2% in month 8 after which the gap decreases steadily, even reaching small positive values of around 0.2% for the last 10 months of the period. There is a dramatic fall in the day-case waiting list of 9.7% in month 4. However, this difference is 0% already in month 10, after which it becomes positive, reaching values of around 1% before declining to 0.2% at the end of the period. The inpatient waiting list is 5.3% smaller in month 4, the gap steadily decreasing to –0.4% at the end of the period. There is again a strong effect on the number of inpatient emergency admissions, with a difference of –3.3% in month 5, the gap getting smaller steadily after month 9 to reach –0.4% in the last month of the period. In contrast to Hospital 1, at Hospital 2 the number of day-case admissions is more affected than the number of inpatient admissions. The number of day-case admissions is 3.8% smaller than it otherwise would have been in month 4, but this difference becomes small and positive in month 12, after which it is positive at around 0.35%, following the day-case waiting list pressures closely. The number of inpatient admissions is 1.3% smaller in month 4, the gap getting almost 0 from month 16 onwards. As at Hospital 1, there is increased outpatient activity, the number of outpatient visits 1.2% higher in month 11 after which it slowly decreases to almost 0 in the last month of the period.

Table 8. Estimation results for time series analysis, Orthopaedics, Hospital 1

IA			DA			EMIA			OV				
EMIA	-0.4813		DA_1	0.3118		IA_1	-0.1435		EMIA	-.2481			
OV_3	0.2998		WLI_4	-0.6957		WTIM_4	0.3471		OV_1	-.2409			
WLI_2	0.6252		WLD_4	0.4215		WDOM_3	0.2361		OV_3	.2782			
WTIM_2	0.7587		WTD5_1	0.2829		IA H2	-0.1464		WLI_1	-.1266			
FBBeds_1	-0.1699					EMIA H2	0.6197						
						WLD_4 H2	0.2105						
WLI			WLD			WTIM			WTD5			WDOM	
IA	-0.1435		DA	-0.1822		IA	-0.0758		IA_2	0.1442		IA_2	0.1390
WLI_1	0.8425		WLD_1	0.9070		DA_3	0.0480		DA_1	-0.2326		EMIA_1	0.1459
WLD_2	0.0602					EMIA	0.0940		WLD_1	0.2907		OV_1	-0.1558
LOSM_2	0.0658					WLI_1	0.3678		WTD5_1	0.3360		WLD_2	0.1553
FBBeds	0.0489					WTIM_1	0.5785					WDOM_2	0.4875
FBBeds			LOSM										
DA	-0.2989		EMIA_2	0.2843									
			LOSM_1	0.3767									

Note to Table 8: All variables are measured in natural logarithms

Table 9. Estimation results for time series analysis, Orthopaedics, Hospital 2

IA			DA			EMIA			OV				
OV_2	0.2774		WLD_1	0.3193		IA_2	-0.1031		OV_4	0.2797			
WLI_1	0.2154		WDIM_4	-0.2456		WLD_1	0.1262		WDDM_3	-0.2251			
			WDDM_3	0.4585		WDIM_2	0.2121		WDOM	0.1965			
			LOSM	0.1986		WDDM_3	0.1383						
						WDOM_2	0.2323						
						WDOM_4 H1	0.2778						
WLI			WLD			WDIM			WDDM			WDOM	
IA	-0.2285		DA	-0.1846		IA	-0.2243		DA	-0.1851		WLD_4	0.1495
EMIA_1	0.1119		DA_1	-0.2229		IA_2	-0.1260		EMIA_3	0.5177		WDOM_1	0.3199
OV_3	0.1277		OV_3	0.1851		WLI_4	0.6442		WLD_2	0.4041			
WLI_1	0.8827		WLD_1	0.8936									
LOSM													
WDI5	0.2599												

Note to Table 9: All variables are measured in natural logarithms

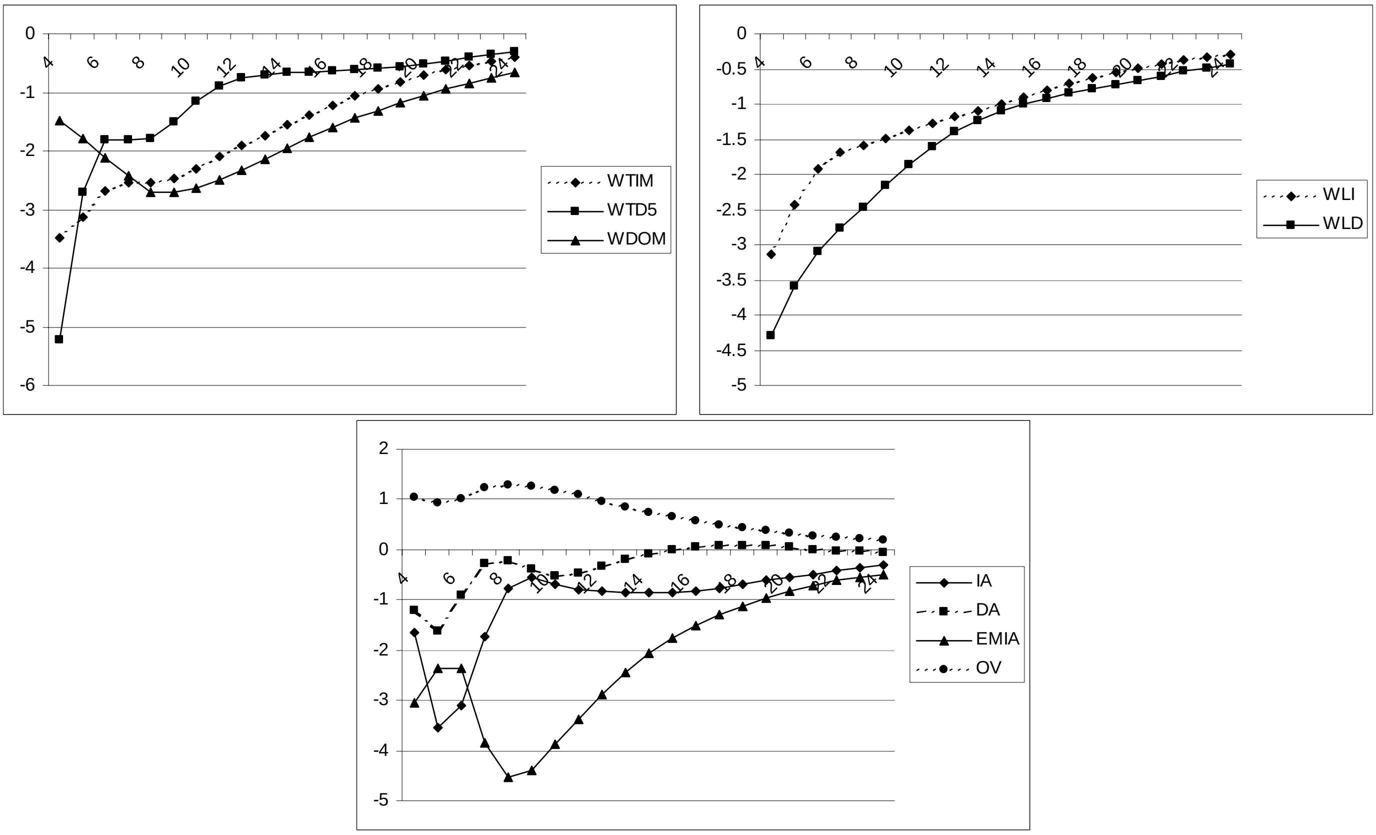

Figure 4. Effects on activity and waiting lists/times after an exogenous 3 months 10% increase in elective inpatient and day-case admissions, orthopaedics, Hospital 1.

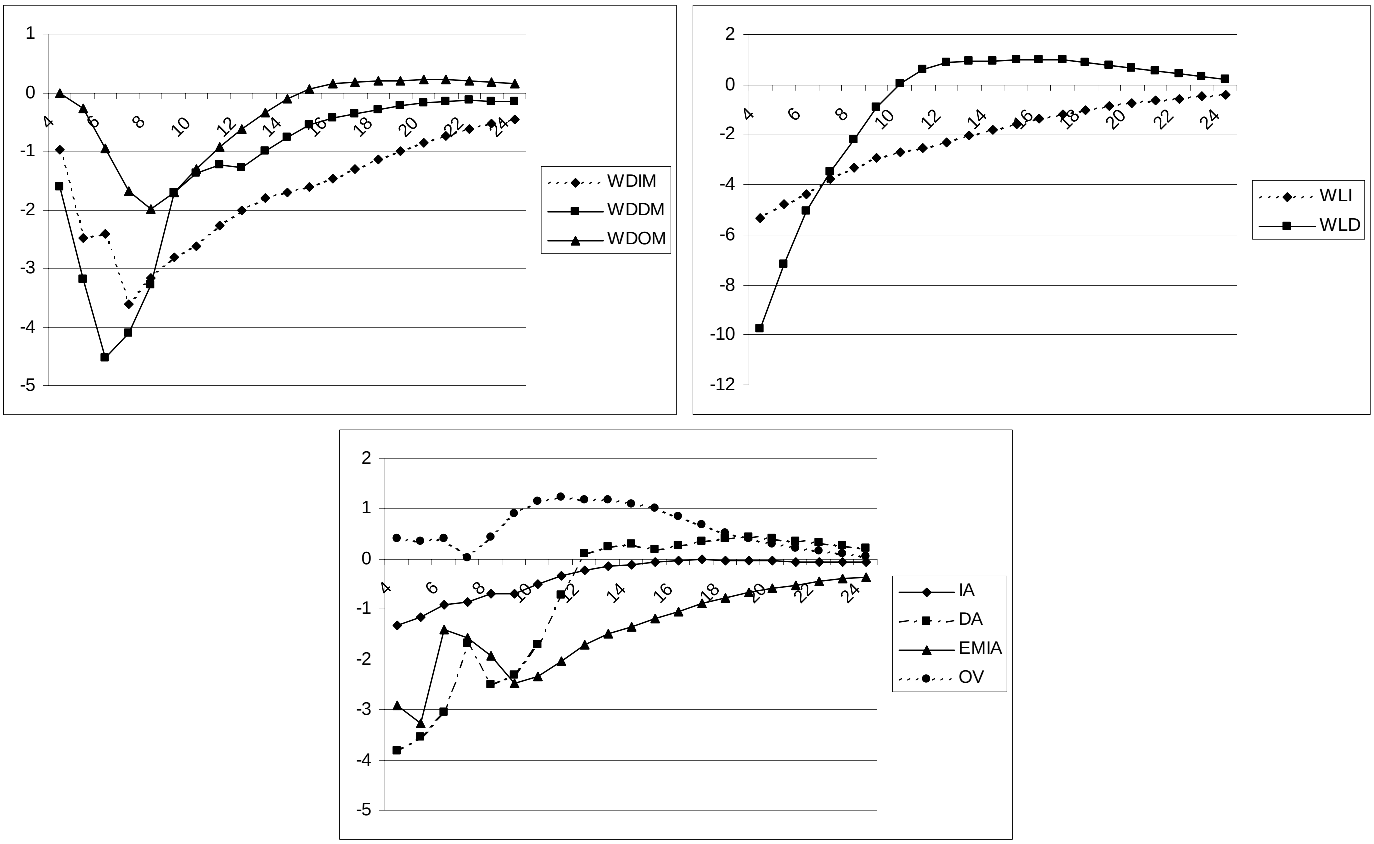

Figure 5. Effects on activity and waiting lists/times after an exogenous 3 months 10% increase in elective inpatient and day-case admissions, orthopaedics, Hospital 2.

7. Conclusions

This paper has given a detailed account of time series analyses of empirical models for supply, waiting lists and waiting times at the hospital/specialty level for two hospitals in a Scottish region. A demand specification was also estimated using GP practice level information on the realised outpatient visits rate per GP practice over time. The empirical specifications found are often close to what is expected from the theoretical models as developed by Gravelle, Smith and Xavier (2000), and the estimation procedures resulted in often very plausible values of estimated elasticities. These estimation results could therefore be meaningfully combined together in order to perform a simulation exercise to assess the responses to activity levels and waiting measures to exogenous increases in the number of elective inpatient and day-case admissions. Such a simulation exercise takes account of all the relationships and feedbacks found between the various activity levels and waiting measures that create a complex picture as highlighted in Figure 1. It thus summarises the multitude of supply and demand responses in the system as they have occurred in the past.

Some important issues could not be addressed by this project. For example, the age-profile of the area population did hardly change over the limited five-year time span of the analysis. We could therefore not assess the impacts of an ageing population on the demand for health care. The GP practice level data could identify age effects from the differences *between* GP patient populations, but the estimation results were very inconclusive.

We further found that there was no detailed data for a long enough period on so-called bed-blocking by elderly patients who could not be discharged to care homes due to shortages in supply. We could therefore not assess the impact on hospital resources of improved community care for the elderly. These data need to be collected systematically and over a long time period in order to assess these implications.

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