THE UNIVERSITY of York

Discussion Papers in Economics

No. 2008/02

Do waiting times reduce hospital costs?

By

Luigi Siciliani, Anderson Stanciole, Rowena Jacob

Department of Economics and Related Studies
University of York
Heslington
York, YO10 5DD

Do waiting times reduce hospital costs?*

Luigi Siciliani[†] Anderson Stanciole[‡] Rowena Jacobs[§]

December 17, 2007

Abstract

Using a sample of 137 hospitals over the period 1998-2002 in the English National Health Service, we estimate the elasticity of hospital costs with respect to waiting times. Our cross-sectional and panel-data results suggest that at the sample mean (103 days), waiting times have no significant effect on hospitals' costs or, at most, a positive one. If significant, the elasticity of cost with respect to waiting time from our cross-sectional estimates is in the range 0.4-1. The elasticity is still positive but lower in our fixed-effects specifications (0.2-0.4). In all specifications, the effect of waiting time on cost is non-linear, suggesting a U-shaped relationship between hospital costs and waiting times: the level of waiting time which minimises total costs is always below ten days.

Keywords: Waiting times; Costs; Hospitals.

JEL Classification: I11; I18

*We thank Jan Erik Askildsen, Tor Iversen, Sverre Kittelsen, Michael Hoel, Eric Nævdal, Peter C. Smith and other seminar participants at the University of Oslo for helpful comments and suggestions.

†Department of Economics and Related Studies, and Centre for Health Economics, University of York, Heslington, York YO10 5DD, UK; and C.E.P.R., 90-98 Goswell Street, London EC1V 7DB, UK. E-mail: ls24@york.ac.uk.

‡*Corresponding author.* European Centre for Social Welfare Policy and Research, Berggasse 17, A-1090 Wien, Austria; Department of Economics and Related Studies, University of York, Heslington, York YO10 5DD, UK. E-mail: stanciole@euro.centre.org.

§Centre for Health Economics, University of York, Heslington, York YO10 5DD, UK; E-mail: rj3@york.ac.uk.

1 Introduction

Waiting times are a major policy issue in many OECD countries. Average waiting times range between four and eight months for common procedures like cataract and hip replacement. There are at least two rationales for explaining the existence of waiting times. The first is that waiting times act as a rationing mechanism that help to bring into equilibrium the demand for and the supply of health care (Lindsay and Feigenbaum, 1984; Martin and Smith, 1999; Cullis, Jones and Propper, 2000): in the absence of price rationing and if benefit from treatment is to some extent unobservable, waiting times may deter patients with small benefit from asking for treatment. A second rationale is that waiting times reduce the cost of provision of elective surgery. When demand is stochastic, waiting times may reduce idle capacity, therefore inducing a more efficient use of resources (Iversen 1993, Iversen 1997, Barros and Olivella 2005). This argument is likely to hold when waiting times are low: hospital cost reduces with waiting times as a consequence of the lower excess capacity. However, as suggested by Iversen (1993), there might be a point over which higher waiting times increase costs, which may be due to the higher costs of managing the waiting list. For example when waiting times are very long, there might be an increase in the resources needed for repeated examinations of patients (since their status might change during the course of the waiting), an increase in treatment costs and in length of stay (if severity deteriorates while waiting), and an increase in cancellation rates. There is therefore, at least theoretically, a level of waiting time which minimises total costs. Above this level, higher waiting times increase hospital costs.

The purpose of this paper is to empirically estimate the elasticity of hospital costs with respect to waiting times. We use a sample of 137 acute hospitals over the period 1998-2002 in the English National Health Service (NHS). Our cross-sectional and panel-data results suggest that at the sample mean (103 days), waiting times have no significant effect on hospitals' costs or, at most, a positive one. If significant, the elasticity of cost with respect to waiting time in our cross-sectional estimates is in the range 0.4-1. The elasticity is still positive but lower in our fixed-effects specifications (0.2-0.4). In all specifications the effect of waiting time on cost is non-linear, suggesting a U-shaped relationship between hospital costs and waiting times, which is consistent with the Iversen (1993) model. The level of waiting times which minimises total costs is always below ten days.

Our results therefore suggest that the level of waiting times observed in our sample is above the one which minimises total costs. If healthcare providers could ration the demand by dumping or neglecting treatment to patients with low expected benefit (explicit rationing), we should not observe providers with waiting times held above the cost-minimising level. However, if waiting times also have a rationing role, then waiting times might as well be above the cost-minimising level. There might be several reasons why explicit rationing might not be feasible for the providers: the benefit for the patients might be at least to some extent unobservable; even if benefit is perfectly observable, patients with low expected benefit might feel entitled to treatment in the NHS: clinicians might therefore prefer to add patients on the waiting list, rather than taking responsibility for explicitly declining treatment to patients. Therefore, our model indirectly supports the theories that model waiting time as a demand-rationing mechanism.

The study is organised as follows. The next section presents the methods. Section 3 describes the data. The results are presented in section 4. Section 5 concludes.

2 Methods

Define C as the total cost of a representative hospital, w as the waiting time of the patients admitted for treatment, and y as the number of patients treated. Following Iversen (1993, 1997), the cost function of a hospital can be represented by

$$C = C(w, y) \tag{1}$$

with $C_y > 0$: higher activity increases costs; $C_w < 0$ if $w < \widetilde{w}$, $C_w = 0$ if $w = \widetilde{w}$ and $C_w > 0$ if $w > \widetilde{w}$. The relationship between waiting times and costs is U-shaped: waiting times reduce costs for low levels of waiting times, while waiting times increase costs for high levels of waiting times. Iversen (1993, 1997) argues that for low waiting times, higher waiting times reduce hospital costs, as a consequence of lower excess capacity: if the demand for health care is stochastic, higher waiting times reduce the probability that the system has idle capacity and therefore reduce costs (for a formal model with a stochastic demand function and the effect of waiting times on idle capacity, see also Goddard, Malek and Tavakoli (1995); Olivella (2003) also assumes that waiting times reduce costs because waiting times allow for a more efficient use of hospital equipment).

Iversen (1993) suggests that there is a level of waiting times over which higher waiting times increase costs. For high waiting times, the reductions in costs from a marginal increase in waiting, in terms of lower probability of idle capacity, become negligible. In contrast, for high waiting times, a marginal increase in waiting may increase the costs of managing the waiting list: for example, more resources might be needed for repeated examination of patients (if the health status of the patients deteriorates in the course of the waiting); treatment costs might increase due to higher cancellations rates if patients scheduled for treatment have in the meanwhile found treatment somewhere else; therefore overall prioritisation costs will be higher when waiting times are higher.

There is then, at least theoretically, a level of waiting time which minimises total costs. The purpose of this paper is to estimate empirically the relationship between hospital costs and waiting times. As far as the authors are aware, this paper is the first that estimates empirically such a relationship. We estimate three types of regressions: pooled OLS, panel fixed effects and panel random effects. The pooled OLS model is given by:

$$C_{it} = \alpha + \gamma_1 w_{it} + \gamma_2 \left(w_{it}\right)^2 + \mathbf{y}_{it}'\boldsymbol{\beta}_1 + \mathbf{x}_{it}'\boldsymbol{\beta}_2 + \mathbf{d}_t'\boldsymbol{\beta}_3 + u_{it} \tag{2}$$

where C_{it} is the cost of hospital i at year t, w_{it} is waiting time, $\mathbf{y}_{it}$ is a vector of outputs, $\mathbf{x}_{it}$ is a vector of control variables, $\mathbf{d}_t$ is a vector of time dummies, and u_{it} is the idiosyncratic error. According to the theoretical literature discussed above, we should expect $\gamma_1 < 0$ and $\gamma_2 \geq 0$.

An alternative approach is to assume that individual effects are specific to each observation. This leads to the fixed effects model:

$$C_{it} = \alpha_i + \gamma_1 w_{it} + \gamma_2 (w_{it})^2 + \mathbf{y}'_{it}\boldsymbol{\beta}_1 + \mathbf{x}'_{it}\boldsymbol{\beta}_2 + \mathbf{d}'_t\boldsymbol{\beta}_3 + u_{it} \quad (3)$$

The hospital-specific fixed-effects α_i capture individual unobserved heterogeneity. An alternative to the fixed effects is the random-effects models, where $\alpha_i \backsim N(\alpha, \sigma_\alpha^2)$ and $u_{it} \backsim N(0, \sigma_\varepsilon^2)$. In this formulation the individual effects are randomly iid distributed over the population of hospitals. Fixed-effects and random-effects models can be compared by the Hausman test, which tests for systematic differences in coefficients between the two models (Cameron and Trivedi, 2005).

It might be argued that the relationship between costs and waiting times is endogenous. If a hospital has high costs, it is more likely to have longer waiting times. There are several channels through which this may happen.

First, more inefficient hospitals have higher costs (due for example to poor management): if higher inefficiency also implies higher inefficiency in the management of the waiting list, then inefficient hospitals may have both higher costs and higher waiting times (a positive correlation). If the researcher has no access to variables correlated with inefficiency, then the OLS estimates of Equation (2) will be biased upwards. We use at least two control variables that might be correlated with inefficiency: length of stay and proportion of day cases. Keeping other factors constant, more inefficient providers have a higher length of stay and a smaller proportion of day cases.

Second, hospitals with higher quality might have a higher cost and at the same time attract a higher number of patients, which leads to a higher waiting time (again, a positive correlation). We use at least two control variables that might be correlated with quality: length of stay and (age and gender adjusted) readmission rates. Keeping other factors constant, providers with higher quality should have a higher length of stay and lower readmission rates.

If there is some residual unobserved efficiency and quality, the OLS might still be biased. However, by estimating a fixed effects model, all unobserved inefficiency and unobserved quality will be captured by the individual fixed effects, as long as quality and inefficiency are time invariant, which seems plausible over short intervals of time.

3 Data

The sample comprises 137 English NHS acute hospitals observed annually between 1998/1999 and 2001/2002, making an unbalanced panel with 440 observations.

The data were collected from several sources, including the Hospital Episodes Statistics (HES), the Department of Health (DoH), the National Health Service Information Authority (NHSIA) and Dr Foster, the independent organization that provides information on the quality of health services.

Our dependent variable is total hospital cost, measured in thousands of Pounds Sterling. It was compiled from the Department of Health and was transformed into real values for 2002 using the GDP deflator provided by HM Treasury. Our measure of waiting times is the mean wait for elective admissions, which was provided by HES. It measures the average number of days between the decision of being admitted to the waiting list and the actual admission for treatment.

Table 1 provides a description of the variables employed in the analysis and corresponding sources of data. We divide the explanatory variables into six groups. Hospital activity is measured by the total number of inpatient spells and the total number of outpatient attendances. Both variables are measured in 1,000 cases. A second group of variables captures the severity of cases treated by the hospital and the demand on resources. It includes emergency admissions as a proportion of total spells and a HRG (Healthcare Resource Group) casemix index based on reference costs (this is equivalent to the case-mix adjustments based on DRGs in other countries, like the Medicare Programme in the US or Italy).

Hospital costs also depend on the efficiency in the use of resources. We control for the number of day cases as a proportion of elective surgeries and the average length of stay. More efficient hospitals are expected to have a higher proportion of surgeries carried out on a day case basis, and a lower average length of stay. The capital stock is proxied by the number of available beds (Vita, 1990; Jacobs, Smith and Street, 2006, p.31) .

The quality of services is proxied by the percentage of emergency readmissions within 28 days from treatment. This variable is standardised by age and gender. Finally, the degree of competition in the geographical market is measured through the number of hospitals within a 20km radius (Propper, Burgess and Green, 2004; Siciliani and Martin, 2007). We do not include salaries because information is not readily available. Also, salaries are nationally agreed and therefore there is little variation in salary expenditure across hospitals.

Table 2 presents some descriptive statistics. The average hospital in the sample has a total cost of just below £105 million per year and an average waiting time for elective surgery of 103 days. It provides around 56,000 inpatient spells and 215,600 outpatient attendances, and faces the competition of 4.5 other hospitals in a 20km radius. Around 36% of inpatient spells are originated as emergency attendances, and the average HRG casemix index is at 93.7 (with a higher inidex indicating a more complex mix of cases). With respect to the efficiency of resource use, each hospital admits on average 50% of the elective patients as day cases, with an average length of stay of 5.3 days. The proportion of emergency readmissions within 28 days is around 6%.

With the exception of emergency admissions, readmissions and day cases, all the other continuous variables (including total cost and waiting times) are included in the log scale, which reduces skewness and allows the interpretation of coefficients as elasticities. Emergency admissions, readmissions and day cases are kept in levels. Since they are measured as percentages, the associated coefficients can also be interpreted as elasticities. After the log transformation, the mean total cost in the sample is equal to the median.

4 Results

The results of the regression analysis for pooled OLS and fixed effects are reported in tables 3 and 4. The dependent variable in both regressions is the log of total hospital cost (lntotcost) in real values of 2002.

Table 3 shows the OLS results for seven different specifications. We add regressors progressively in order to test the stability of results. The basic regression (column (1)) includes mean waiting times (linear and quadratic effect) and activity indicators (inpatient spells and outpatient attendances), and controls for the HRG index, London effect and year. We then progressively add controls for capital stock (available beds (2)), demand on resources (emergency admissions (3)), efficiency on use of resources (daycases (4) and average length of stay (5)), quality of service (emergency readmissions (6)) and competition (number of competitors in a 20 km radius (7)). Given the limited coverage of our sample, the inclusion of the quality and competition indicators reduces significantly the number of observations. In Table 4 there are only six specifications for panel regressions because the competition indicator, the HRG index and the London dummy either do not vary or vary little over time, which prevents fixed effects estimations.

We initially estimated the regressions using a translog specification, which is a second-order Taylor approximation adding squared terms for the activity indicators. However, since the square and cross terms were not significant (apart from the squared waiting-time effect), we decided to exclude them from the final specification. The OLS regressions were estimated using standard errors robust to both heteroscedasticity and the serial correlation among observations of the same hospital over the years. Thus we report both the total number of observations (N) and the number of clusters (N *clusters*).

Table 3 reports pooled cross-section estimates using unbalanced samples. By 'unbalanced' we mean that as additional regressors are added the sample size decreases, falling from 440 observations in the basic regression to 319 observations in the regression with all independent variables.

All the regressions have been estimated with both linear and quadratic effects for waiting times, which allows us to control for nonlinearities in the hospital cost response to waiting times. Two reasons guided the choice of this functional form. First, it gives a direct test of Iversen's suggestion of a nonlinear effect of waiting times. As explained in

Section 2, we should expect to find a negative coefficient for low levels of waiting times and a positive coefficient for high levels. Second, the inclusion of a quadratic effect of waiting times eliminates misspecification problems. In all the specifications in Table 3 the RESET test is not significant, which suggests that the functional form is correctly specified.

Let us now focus on the coefficients estimated by the regressions, starting with waiting times. In all regressions the coefficient for the linear component is negative, while the quadratic is positive. This implies that waiting times have an initial negative impact on costs. However, after some point the effect is reversed and waiting times start to increase costs. Therefore, in principle there is an optimal level of waiting times that minimises total costs (this optimal level is calculated below).

Although the effect of waiting times is consistent with the theory, the estimated coefficients are not always statistically significant. In the basic regression (column (1) of Table 3), the estimated effect of waiting times is not significant, either jointly or separately. However, the other variables display significant effects. As expected, both inpatient and outpatient activity increase cost, as does the HRG index. On average, hospitals costs in London are approximately 20% higher than in the rest of the country. Real costs increased significantly between 1998 and 1999, possibly due to nation-wide salary increases from 1999/2000 onwards.

Adding available beds (column (2)) affects the results, and the coefficients of waiting times become significant. The effect of available beds, our proxy for capital, is itself positive in all regressions where it is included.

The introduction of emergency admissions or day cases does not affect the results significantly (see columns 3 and 4). Emergency admissions have no effect on hospital costs. Day cases have a negative and significant coefficient, suggesting that hospitals with a higher proportion of elective admissions treated as day cases have lower costs. In column (5), we add average length of stay, which has a positive and significant effect on hospital costs, as expected. The effect of waiting times is not altered and the RESET test is still not significant.

Next we include readmission rates (column (6)), which has a positive but not statistically significant effect on hospital cost. In sharp contrast with previous specifications, the effects of waiting times and available beds cease to be significant. One possible explanation for this result is that adding readmission rates causes a sizable reduction in the sample, making the effect of waiting time insignificant. Another explanation is that lower readmission rates (higher quality) generate both higher costs and higher waiting times (through lower demand). But column (7) suggests that the effect of readmission has no significant effect on costs. Also the positive coefficient on readmission rates suggests that lower readmission would reduce costs (in contrast with what we would expect). We therefore favour the first explanation.

Finally we evaluate the effect of local competition from other hospitals (column (7)). The estimated effect of competition is negative, although not significant.

From Table 3 it is not immediate to infer whether the effect of waiting time on costs is positive or negative when evaluated at the sample mean. Recall that at the sample mean the waiting time is 102.9 days. Differentiating the equation in Column (3), we obtain $\varepsilon_w^C = \partial \log C_{it}/\partial \log w_{it} = -0.93 + 2 * 0.21 * \log(102.9) = 1.02$. Therefore, the elasticity of cost with respect to waiting time is markedly positive. Using similar computations, we can show that the elasticity is smaller for Column (5), $\varepsilon_w^C = 0.75$, and even smaller for Column (7), $\varepsilon_w^C = 0.37$.

It is also of interest to calculate the level of waiting time which minimises total costs. By setting $\partial \log C_{it}/\partial \log w_{it} = 0$ from Columns (3), (5) and (7) we obtain a waiting time respectively equal to 9.2, 9.8 and 7.4 days. Therefore, if waiting times reduce costs for low levels of waiting times, this effect vanishes after waiting time has reached less than ten days.

In addition to the pooled cross-sectional analysis we also estimate fixed- and random-effects panel regressions. Results from the fixed-effects estimations are reported in Table 4. Notice that the time-invariant regressors (like London dummy and number of competitors) are excluded from the fixed-effects regressions. The effect of waiting times estimated by fixed-effects is qualitatively similar to the pooled OLS case, with a negative coefficient for the linear component and a positive coefficient for the quadratic one. However, the coefficients are not significant (although jointly significant in Columns (1) and (2)). This might be due to the inefficiency of the fixed-effects estimator. A more efficient model is the random-effects estimator but this will give unbiased estimates only if the individual-specific effects are not correlated with the independent variables. The Hausman test rejects the random effects model: individual-specific effects are therefore correlated with independent variables. Nevertheless, the random-effects model might provide an idea on the degree of inefficiency of the fixed-effects model. We therefore report in Table 5 also the random effects estimations. In most specifications the effect of waiting times is significant and in accordance with the hypothesis proposed by Iversen (1993). The linear coefficient of waiting times is negative, but the quadratic one is positive, suggesting that increasing waiting times up to a certain level decreases costs, but past this level the effect is reversed. The elasticity of cost with respect to waiting time ($\varepsilon_w^C = \partial \log C_{it} / \partial \log w_{it}$) is always positive at the sample mean for both the fixed and the random effects models, respectively in the range 0.21-0.37 for the fixed effects and 0.31-0.85 for the random effects. Again, the level of waiting time which minimises total costs is below ten days.

5 Conclusions and policy implications

Waiting times are a significant feature of several healthcare systems. This paper has investigated the effect of waiting times on hospital costs. Iversen (1993) has argued that for low waiting times, higher waiting times reduce costs due to lower idle capacity, but there might be a point over which higher waiting times increase costs, due to the higher costs of managing the waiting list. Using a sample of 137 acute hospitals over the period 1998-2002 in the English National Health Service (NHS) we have tested empirically the relationship between hospital costs and waiting times. Our cross-sectional and panel-data results suggest that at the sample mean (103 days), waiting times have no significant effect on hospitals' costs or, at most, a positive one. Our model indirectly supports theories which model waiting times as a mechanism to ration demand. If demand could be rationed explicitly, waiting times should be below or at most equal to the cost minimising level, which is in contrast with our findings. Although our results suggest that waiting times might have a strong rationing rationale, they do not imply that waiting times are an optimal rationing system. As pointed out for example by Barzel (1974), waiting times generate a loss to patients but do not generate benefits for the providers (at least if waiting time is weakly above the cost-minimising level). If expected benefit was perfectly observable by the provider, an ideal rationing mechanism would provide swift treatment to patients with high expected benefit, refuse treatment to patients with low expected benefit, and set a waiting time which is strictly below the cost minimising level. Recent policies that focus on the development of explicit prioritisation criteria (Siciliani and Hurst, 2005) might encourage clinicians in the future to rely more on explicit rationing and less on waiting-time rationing.

6 References

Barros, P. and Olivella, P., 2005, Waiting lists and patient selection, *Journal of Economics and Management Strategy,* 14(3), 623–646.

Barzel, Y., 1974, A theory of rationing, *Journal of Law and Economics*, 17, 73-95.

Cameron, A. C. and Trivedi, P., 2005, Microeconometrics - Methods and applications, Cambridge University Press, New York.

Cullis, J., Jones, P. and Propper, C., 2000, Waiting lists and medical treatment: Analysis and policies, in A. Culyer and J. Newhouse (eds), *Handbook of Health Economics*, Elsevier, Amsterdam, chapter 23.

Goddard, J., Malek, M., Tavakoli, M., 1995, An economic model of the market for hospital treatment for non-urgent conditions, *Health Economics*, 4(1), 41-55.

Iversen, T., 1993, A theory of hospital waiting lists, *Journal of Health Economics,* 12(1), 55–71.

Iversen, T., 1997, The effect of a private sector on the waiting time in a national health service, *Journal of Health Economics,* 16(4), 381–396.

Jacobs, R., Smith, P.C., and Street, A., 2006, Measuring efficiency in health care, Cambridge University Press.

Lindsay, C. and Feigenbaum, B., 1984, Rationing by waiting lists, *The American Economic Review,* 74(3), 404–417.

Martin, S. and Smith, P.C., 1999, Rationing by waiting lists: An empirical investigation, *Journal of Public Economics,* 71(1), 141–164.

Olivella, P., 2003, Shifting public-health-sector waiting lists to the private sector, *European Journal of Political Economy*, 19(1), 103-132.

Propper, C., Burgess, S. and Green, K., 2004, Does competition between hospitals improve the quality of care?: Hospital death rates and the NHS internal market, *Journal of Public Economics*, 88 (7-8), 1247-1272.

Siciliani, L. and Hurst, J., 2005, Tackling excessive waiting times for elective surgery: a comparison of policies in twelve OECD countries, *Health policy,* 72, 201-215.

Siciliani, L. and Martin, S., 2007, An empirical analysis of the impact of choice on waiting times, *Health Economics*, 16(8), 763-779.

Vita, M., 1990, Exploring hospital production relationships with flexible functional forms, *Journal of Health Economics,* 9(1), 1109–1119.

Table 1: Description of variables

Variable name	Description	Source*
(a) Hospital cost		
totcost	Total hospital cost (£000)	DoH
	(2002 real values using Treasury GDP deflator)	
(b) Waiting times		
meanwait	Mean wait in days	HES
(c) Measures of activity		
totspells	Total inpatient spells (000)	HES
totop	Total outpatient attendances (000)	DoH
(d) Case mix		
emergadm	Number of emergency admissions as % of total inpatient spells	HES
hrgindrc	HRG casemix index based on Reference Costs	NHSIA
(e) Efficiency on use of resources		
daycase	Number of day cases as % of elective admissions	HES
alos	Average length of stay	HES
(f) Capital inputs		
avbeds	Number of available beds	DoH
(g) Quality of services		
readmisnpc	Emerg. readm. % within 28 days, all ages, age sex std	DoH
(h) Competition		
nhosp20km	Number of hospitals within 20 km radius	
(i) Dummy variables		
london	Trust is in London	CIPFA

* DoH: Department of Health, HES: Hospital Episodes Statistics, NHSIA: National Health Service Information Authority, CIPFA: The Chartered Institute of Public Finance and Accountancy

Table 2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
totcost	440	104,731.5	42,563.7	26,096.4	260,045.0
meanwait	440	102.9	29.9	17.0	219.0
totspells	440	56.0	22.4	4.2	131.4
totop	440	215.6	87.8	35.5	609.3
emergadm	440	36.1	5.1	4.5	65.0
hrgindrc	440	93.7	7.1	75.5	163.4
daycase	439	50.1	8.0	0	77.2
alos	440	5.3	1.7	2.5	28.9
readmisnpc	385	5.8	0.9	3.7	10.2
avbeds	440	681.8	255.2	166.0	1,574.7
nhosp20km	359	4.5	4.8	1	19
london	440	0.1	0.4	0	1
y1998	440	0.3	0.4	0	1
y1999	440	0.3	0.4	0	1
y2000	440	0.2	0.4	0	1
y2001	440	0.2	0.4	0	1

Table 3: Unbalanced pooled OLS regressions of total hospital cost

Dependent variable: log(totcost); Robust standard errors

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lnmeanwait	- 1.40	-0.93*	-0.93*	-0.76*	-0.73*	- 0.28	- 0.28
$(\text{lnmeanwait})^2$	0.29	0.21*	0.21**	0.17*	0.16*	0.07	0.07
lntotspells	0.55***	0.3***	.27***	0.28***	0.34***	0.62***	0.65***
lntotop	0.38***	0.28***	0.28***	0.28***	0.29***	0.23***	0.24***
lnhrgindrc	1.2***	0.81***	0.83***	0.8***	0.77***	0.73***	0.72***
lnavbeds		0.4***	0.43***	0.42***	0.35***	0.14	0.10
emergadm			-0.003	-0.003	-0.003	-0.021	-0.011
daycase				-0.002	-0.003*	-0.004**	-0.003*
lnalos					0.08	0.25***	0.26**
readmisnpc						0.002	0.004
lnnhosp20km							-0.002
london	0.19***	0.18***	0.17***	0.16***	0.16***	0.15***	0.15**
y1999	0.13***	0.13***	0.13***	0.13***	0.13***	0.14***	0.15***
y2000	0.19***	0.17***	0.17***	0.17***	0.21***	0.28***	0.28***
y2001	0.14***	0.14***	0.15***	0.15***	0.15***	0.15***	0.14***
constant	4.7**	4.5***	4.4***	4.3***	4.4***	3.9***	3.9***
R^2	0.86	0.89	0.89	0.89	0.89	0.9	0.89
RESET	0.1	0.5	0.5	1	1.2	2	1.8
Joint significance†	1.4	2.04	2.12	1.7	1.57	0.35	0.59
N	440	440	440	439	439	384	319
N_clusters	137	137	137	137	137	109	88

Legend: * p<.1; ** p<.05; *** p<.01; † Test for joint significance of lnmeanwait and lnmeanwait^2

Table 4: Unbalanced fixed effects regressions of total hospital cost

Dependent variable: log(totcost); Robust standard errors

Variable	(1)	(2)	(3)	(4)	(5)	(6)
lnmeanwait	- 0.19	- 0.18	- 0.13	- 0.14	- 0.13	- 0.16
$(\text{lnmeanwait})^2$	0.06	0.06	0.04	0.04	0.04	0.04
lntotspells	0.16*	0.13	0.18**	0.18**	0.19**	0.02
lntotop	0.12*	0.11*	0.11*	0.11*	0.11*	0.10
lnavbeds		0.24***	0.17**	0.17**	0.15**	0.23***
emergadm			0.0068**	0.0065*	0.0061*	0.003
daycase				-0.00082	-0.001	-0.0011
lnalos					0.05	0.05
readmisnpc						- 0.01
y1999	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***
y2000	0.15***	0.14***	0.14***	0.14***	0.16***	0.17***
y2001	0.21***	0.2***	0.19***	0.19***	0.19***	0.2***
constant	10***	9***	8.9***	9***	9***	9.5***
R^2 within	0.67	0.68	0.69	0.69	0.69	0.69
R^2 between	0.71	0.82	0.77	0.77	0.78	0.86
R^2 overall	0.68	0.81	0.77	0.77	0.78	0.76
$corr(\alpha_i, Xb)$	0.64	0.69	0.63	0.65	0.66	0.71
σ	0.3	0.24	0.25	0.25	0.26	0.27
σ_u	0.29	0.23	0.25	0.24	0.25	0.27
σ_e	0.065	0.063	0.063	0.063	0.063	0.063
ρ	0.95	0.93	0.94	0.94	0.94	0.95
Hausman	68.5***	56***	62***	60.5***	59.5***	72.6***
Breusch-Pagan	234.2***	260.4***	249.5***	243.3***	236.7***	241.2***
Joint significance†	5.6***	2.7*	1.9	1.7	1.5	0.5
N	440	440	440	439	439	384
N_clusters	137	137	137	137	137	109

Legend: * p<.1; ** p<.05; *** p<.01; † Test for joint significance of lnmeanwait and lnmeanwait^2

Table 5: Unbalanced random effects regressions of total hospital cost

Dependent variable: log(totcost); Robust standard errors

Variable	(1)	(2)	(3)	(4)	(5)	(6)
lnmeanwait	- 0.72	-0.55*	-0.54*	-0.5*	-0.45*	- 0.24
$(\text{lnmeanwait})^2$	0.17	0.13**	0.13**	0.12**	0.11**	0.06
lntotspells	0.36***	0.18***	0.19***	0.21***	0.24***	0.35***
lntotop	0.31***	0.22***	0.22***	0.23***	0.24***	0.23***
lnavbeds		0.45***	0.45***	0.43***	0.39***	0.35***
emergadm			0.0005	-0.0001	-0.0005	-0.0017
daycase				-.0024*	-.0028**	- 0.0041***
lnalos					0.08	0.11**
readmisnpc						- 0.01
y1999	0.13***	0.13***	0.12***	0.13***	0.13***	0.14***
y2000	0.14***	0.13***	0.13***	0.14***	0.17***	0.19***
y2001	0.18***	0.18***	0.18***	0.19***	0.18***	0.18***
constant	9.8***	7.7***	7.7***	7.8***	7.6***	7***
R^2 within	0.62	0.66	0.66	0.66	0.66	0.65
R^2 between	0.77	0.85	0.85	0.86	0.86	0.9
R^2 overall	0.8	0.86	0.85	0.86	0.87	0.88
σ	0.18	0.16	0.16	0.15	0.15	0.13
σ_u	0.17	0.14	0.14	0.14	0.14	0.11
σ_e	0.065	0.063	0.063	0.063	0.063	0.063
ρ	0.87	0.84	0.84	0.83	0.83	0.75
Joint significance†	9.2**	6.4**	6.2**	5.1*	4.6*	3.8
N	440	440	440	439	439	384
N_clusters	137	137	137	137	137	109

Legend: * p<.1; ** p<.05; *** p<.01; † Test for joint significance of lnmeanwait and lnmeanwait^2