THE UNIVERSITY of York

CHE

Centre For Health Economics

What Explains Variation in the Costs of Treating Patients in English Obstetrics Specialties?

CHE Research Paper 49

What Explains Variation in the Costs of Treating Patients in English Obstetrics Specialties?

Mauro Laudicella[1]
Kim Rosen Olsen[2]
Andrew Street[1]

[1] Centre for Health Economics, University of York, York YO10 5DD, UK
[2] Institute for Public Health, University of Southern Denmark and Danish Institute for Health Services Research, 27-29 Dampfaergevej, DK-2100, Copenhagen Ø. Denmark

July 2009

Background

CHE Discussion Papers (DPs) began publication in 1983 as a means of making current research material more widely available to health economists and other potential users. So as to speed up the dissemination process, papers were originally published by CHE and distributed by post to a worldwide readership.

The new CHE Research Paper series takes over that function and provides access to current research output via web-based publication, although hard copy will continue to be available (but subject to charge).

Acknowledgements

We would like to thank Susan Devlin, Tom Fothergill, Paula Monteith, Nigel Rice, Eileen Robertson and the PbR team at the Department of Health for their advice and assistance. The project was funded by the Department of Health in England as part of a programme of policy research. The views expressed are those of the authors and may not reflect those of the funder.

Disclaimer

Further copies

Printed copies are available on request at a charge of £5.00 per copy. Please contact the CHE Publications Office, email che-pub@york.ac.uk, telephone 01904 321458 for further details.

Centre for Health Economics
Alcuin College
University of York
York, UK
www.york.ac.uk/inst/che

Abstract

We assess patients admitted to English obstetrics departments to identify what proportion of variation in their costs is explained by patient characteristics and what proportion is due to departmental characteristics. Hospital Episode Statistics records for every patient admitted to obstetrics departments are matched to Reference Cost data by HRG reported by all English hospitals for the year 2005/6. Our sample consists of 951,277 patients in 136 departments. We estimate fixed effects models analysing patient-level costs, explore departmental characteristics that drive variation in costs at department-level and explore the sensitivity of results to the use of the full sample and sub-samples of obstetrics patients. Patient costs depend on various diagnostic characteristics over and above the HRG classification, particularly whether the patient suffered infection. After controlling for patient characteristics a substantial amount of unexplained variation in costs remains at departmental level. Higher costs are evident in departments that are not supported by a neonatology specialty and where factor prices are higher. There is evidence of lower costs in departments with high volumes of activity. We identify departments where further scrutiny of their high costs is required.

1. Introduction

It is often asserted that health care organisations face limited competitive pressures that would otherwise encourage them to innovate and adopt cost minimising behaviour. Competitive behaviour may be less in evidence if health care is publicly funded or in situations where organisations enjoy a geographical or specialist monopoly of supply (Bilodeau et al., 2000). When competitive pressure is weak, there may be scope for better utilisation of resources and reductions in cost. But in the absence of competition, pressure to reduce costs must come from another source, such as a regulatory authority or policy-maker. In this context, information on the performance of the health care organizations assumes a key role allowing the policy maker to compensate the absence of competitive markets with correct regulation policies.

There have been numerous studies that examine hospital costs or efficiency (Worthington, 2004, Hollingsworth, 2008, Rosko and Mutter, 2008). Yet despite this proliferation of academic research, it has had limited influence on regulatory policy and its impact on hospital behaviour has been negligible. We contend that this is because comparative analysis of hospitals suffers two drawbacks. First it is very difficult for analysts to make any clear recommendations as to where practical efforts should be directed should one hospital be found more costly or less efficient than another. Hospitals are multi-product organisations and, to take action, management needs to know whether poor performance is a problem in general or is limited to specific product lines. By considering the hospital as a whole, most studies offer limited insight into the source of higher costs or apparent inefficiency.

The second related, but more fundamental, limitation is that it cannot be assumed that a common production function applies across all hospitals. Indeed the majority of hospitals, particularly non-specialist hospitals, house a range of different departments or specialties, each of which can be considered as having a distinct production function. It is difficult to capture these distinctive features in hospital-level analysis, especially when hospitals are quite heterogeneous with respect to their specialty mix. Any failure to observe and control for this heterogeneity will bias the comparative assessment.

In previous work it has been argued that specialty-level analysis is preferable to hospital-level analysis (Harper et al., 2001). This is because each particular specialty is more likely to be undertaking comparable activities, treating similar types of patients and, hence, applying a production technology similar to that in the same specialty in other hospitals. Thus comparing the same specialty across hospitals is more appropriate for both analytical purposes and for informing policy-makers and practitioners about how to respond to the findings. However, research based on specialty-level analysis is uncommon because routine data are rarely available at this level. In this paper, we seek to overcome this drawback by exploiting patient-level data, recognising that patients are clustered within specialties.

The use of patient-level data offers an additional important advantage. In all probability the primary reason why costs vary among hospitals/specialties is because each treats a different mix of patients. Most studies make allowance for expected differences in care requirements by differentiating patients using Diagnosis Related Groups (DRGs) or variants thereof such as the Healthcare Resource Groups (HRGs) used in England. However the classification system used to differentiate between patients can never account for all cost variation. This would not be a problem if differences across providers were random, where it is a matter of chance whether any particular patient is more or less expensive than the average patient in the HRG to which they are classified. With sufficiently large volumes, these differences cancel out. Problems arise if the differences across providers are systematic, with one type of provider more likely to treat low-cost patients and another treating more high-cost patients. For example, teaching hospitals might attract more severe patients within the same HRG categories as compared with other hospitals because of their excellence in providing such treatments; or hospitals located in deprived areas might serve more complex case-mix of patients because of the lower health status of people living in these areas. By using patient-level data, we are able to control for various personal and diagnostic characteristics over and above the HRG to which the patient is allocated when making comparisons of specialty costs, thereby making inferences about performance more robust (Jacobs et al., 2006, Hauck and Street, 2006, Olsen and Street, 2008).

We focus on all obstetrics specialties in England to assess what explains variation in the unit costs of the patients they treat using data for every patient discharged from an obstetrics department during

2005/06. We assess two main questions. Firstly, to what extent are costs explained by the characteristics of patients admitted to obstetrics departments? Secondly, after controlling for patient characteristics, why do some obstetrics departments have higher costs than others? We describe our data in section two, including how we have matched data from different sources. Our econometric approach is described in section three, followed by results in section four. We draw conclusions in section five.

2. Data

We analyse the hospital episode statistics (HES) for all patients discharged from an English obstetrics department in 2005/6. HES comprise individual patient records – defined as a Finished Consultant Episode (FCE) – about every NHS patient treated as a day case or inpatient in England. Each patient record contains socio-demographic (e.g. age, gender, average income in their area of residence) and clinical information (e.g. diagnoses, procedures performed).

We focus on obstetrics departments for two main reasons. First, there is a limited set of HRGs to which obstetrics patients are allocated: the majority (96%) of activity is confined to twelve HRGs (chapter N, comprising neonatal, maternity and antenatal care). Compared to specialties that treat a more diverse set of patients, this should ensure limited heterogeneity in the production process across obstetrics departments. Second, most patients admitted to obstetrics remain under the care of a single consultant during their hospital stay, meaning that activity in obstetrics departments is reasonably self-contained, with patients rarely being transferred to other consultants/specialties. 98% of FCEs in obstetrics are single episode spells, compared to 79% for all HES records (Castelli et al., 2008). This helps ensure that the costs of care are borne solely and fully by the obstetrics department, rather than reflecting joint production with other departments.

From an initial sample of 1,009,747 obstetrics patients our analytical sample is reduced to 951,277 after dropping patients for the reasons detailed in Appendix 1. Each patient record in HES is mapped to cost information supplied by every English hospital according to the process detailed in Appendix 2. This mapping procedure allows us to obtain variation in the cost of treating patients within their HRG classification in each department. Additional variation comes from the method of admission and the excess daily cost identifiable for those with long lengths of stay. For obstetrics departments, variation in patient level cost is illustrated in Figure 1, where each vertical set of points shows the cost of all patients in each obstetrics department. Cost variation is also evident when considering a single HRG, as Figure 2 shows for normal deliveries. Table 1 shows the distribution of activity in obstetrics departments according to HRGs in the N chapter, together with summaries of length of stay and cost.

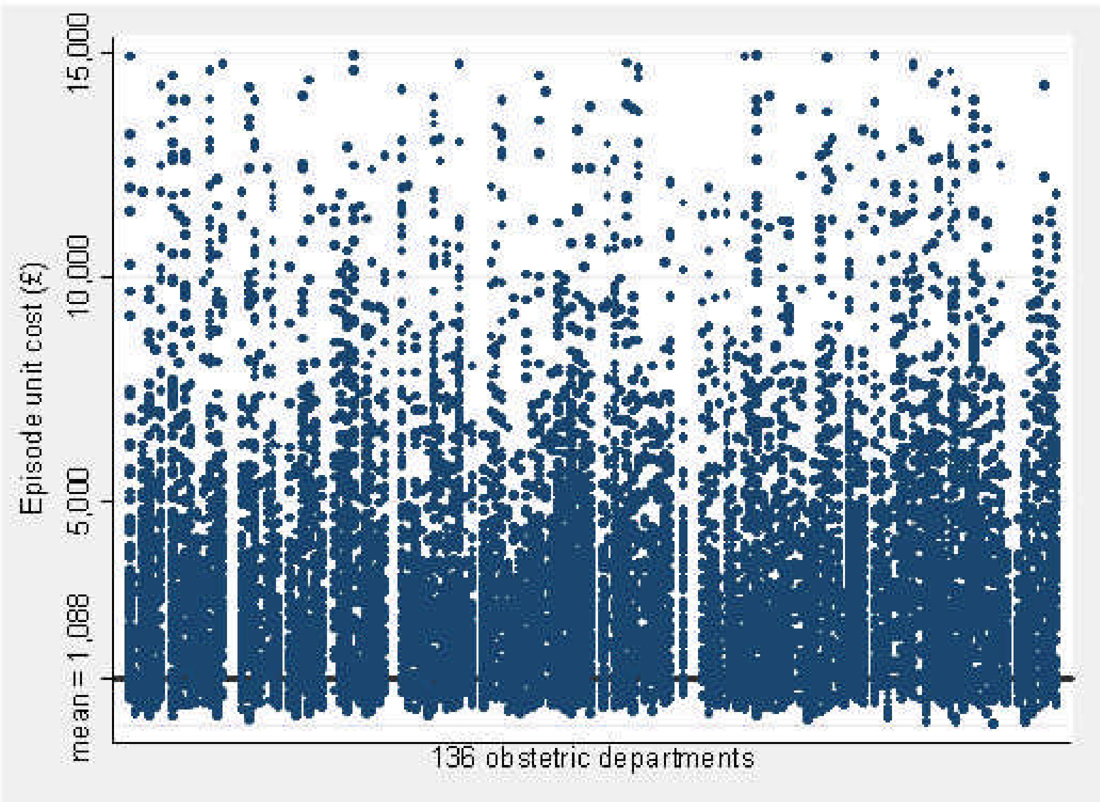

Figure 1: Patient costs by obstetrics department, all obstetrics patients

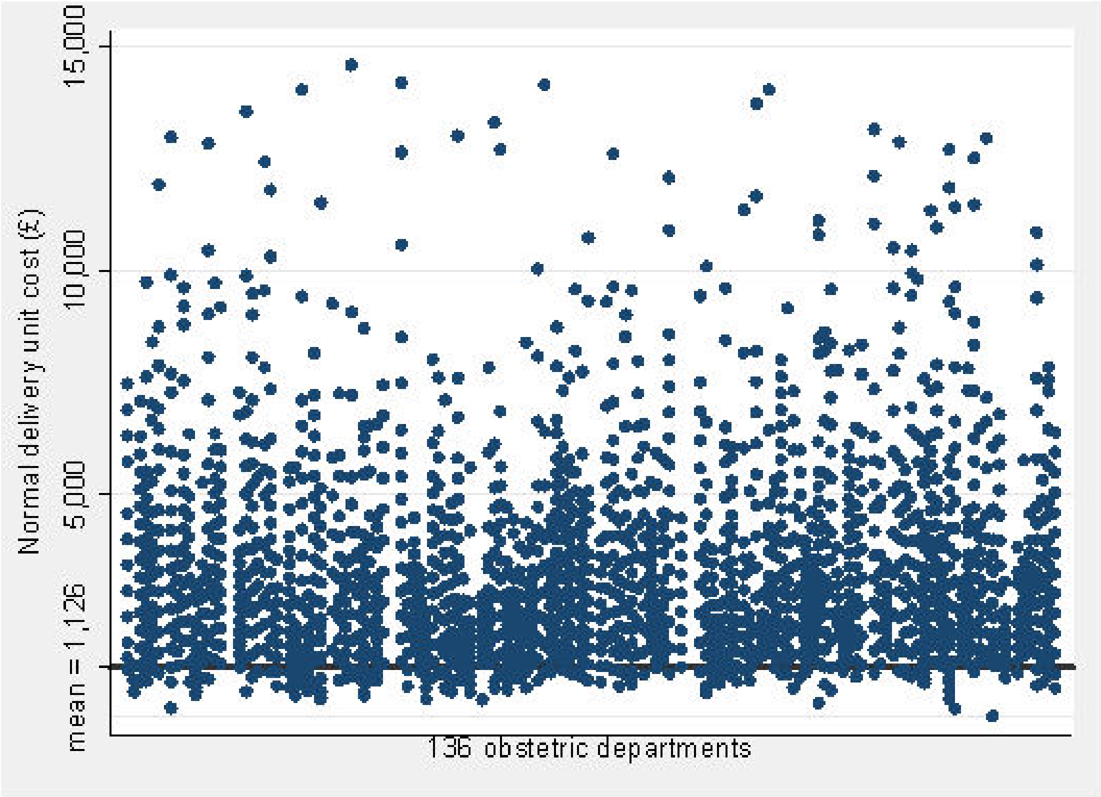

Figure 2: Patient costs by obstetrics department, normal deliveries only

Table 1 Activity in obstetrics departments, by HRG

HRG		Patients	% of all obstetrics patients	% long stay patients	Cost Mean	Cost SD
N01	Neonates - Died <2 days old	252	0.0%	0.0%	716	329
N02	Neonates with Multiple Minor Diagnoses	972	0.1%	0.3%	1,091	201
N03	Neonates with one Minor Diagnosis	6,236	0.7%	0.9%	763	176
N04	Neonates with Multiple Major Diagnoses	30	0.0%	0.0%	830	1,082
N05	Neonates with one Major Diagnosis	184	0.0%	0.0%	777	713
N06	Normal Delivery w cc	20,847	2.2%	4.1%	1,831	765
N07	Normal Delivery w/o cc	251,360	26.4%	20.2%	1,126	526
N08	Assisted Delivery w cc	5,916	0.6%	5.0%	2,240	907
N09	Assisted Delivery w/o cc	50,597	5.3%	4.1%	1,483	463
N10	Caesarean Section w cc	19,072	2.0%	7.4%	3,366	1,310
N11	Caesarean Section w/o cc	97,547	10.2%	5.8%	2,350	834
N12	Antenatal Admissions not Related to Delivery Event	464,972	48.8%	11.5%	647	461
Total N		917,985	96.4%	12.5%	1,100	854
Other	All other HRGs	34,292	3.6%	7.4%	779	623
Total		952,277	100.0%	12.3%	1,088	849

3. Methods

Our main objective is to analyse the variation in costs across departments after taking account of differences in the patients they treat and external factors that might affect departmental costs but that are beyond their control. To do this, we perform a two stage analysis. First we regress patient level costs against a set of patient characteristics that might explain their costs and a departmental fixed effect. From this equation we obtain each department's average cost purged of the influence of the characteristics of their patients. Second we investigate variations in average cost that persist at departmental level using an Estimated Dependent Variable model (EDV).

In the first stage we estimate a fixed effects model of the following form:

$$c_{ij} = \boldsymbol{\beta}_h'\mathbf{h}_{ij} + \boldsymbol{\beta}_k'\mathbf{k}_{ij} + \boldsymbol{\beta}_q'\mathbf{q}_{ij} + \boldsymbol{\beta}_d'\mathbf{d}_{ij} + u_j + v_{ij} \qquad (1)$$

where c_{ij} is the cost for patient i in department j.[1] $\mathbf{h}_{ij}$ is a vector of dummy variables specifying the HRG to which the patient is allocated, with the HRG for a normal delivery (N07) being the reference category[2]; $\mathbf{k}_{ij}$ is vector of variables capturing age and an index of income deprivation of the area where the patient lives; $\mathbf{q}_{ij}$ is a vector of variables specific to obstetrics care, including the number of babies delivered, birth weight, and whether or not the baby was still-born; and $\mathbf{d}_{ij}$ is a vector diagnostic and procedural variables, including counts of diagnoses and operations performed and dummy variables which capture diagnostic characteristics of patients that might explain costs over and above the HRG to which the patient is allocated. These dummy variables are identified by examining the frequency of diagnoses recorded across the diagnostic fields for all the patients in the sample. Table 2 reports the ICD-10 codes used to construct these variables and the number of obstetrics and maternity patients to which they apply.

This equation is estimated for four different samples of patients as a form of sensitivity analysis. The first sample includes all patients admitted to the obstetrics department, the second includes only patients with a length of stay below their HRG-specific trimpoint (trimmed sample), the third includes only patients with a length of stay above their trimpoint (long-stay sample), and the fourth considers only patients receiving maternity care, these being patients allocated to HRGs N06-N11. This analysis allows us to assess if our predictions are sensitive to length of stay outliers, how representative maternity patients are of obstetrics patients in general and whether conclusions about costs across departments are sensitive to what activity is considered. Descriptive details of the explanatory variables for the patients included in each equation are shown in Table 3.

From equation (1) we obtain $\hat{u}_j$, the departmental fixed effect, which can be interpreted as a measure of relative departmental performance after allowing for differences in patient characteristics (Hauck et al., 2003, Bhalotra and Zamora, 2008). Its values express the difference between the average unit cost of a specific department and the population average. Thus, positive values indicate that the average cost per patient in the department in question is above the average.

[1] Although there is evidence of heteroscedasticity in patient costs, transforming costs into logarithmic form is not required to our analysis. OLS provides consistent estimates of departmental fixed effects which are the main objective of our analysis in the first stage. Using log transformation may improve the estimation of the SE, but will result in estimated coefficients based on geometric rather than arithmetic mean. Retransforming such coefficients is not straightforward in the presence of heteroscedasticity (Manning, 1998). We obtain consistent SE by applying the cluster robust estimator.

[2] Rather than dummy variables, it is common to construct a casemix index to capture cost variation across HRGs. Construction requires attaching a resource weight to each HRG to allow aggregation. In this study, the relatively small number of HRGs and large sample size allow us to avoid making assumption about HRG relative weights and, instead, estimate these from the data.

Table 2 Obstetrics patients with particular diagnostic markers

Label	ICD-10 diagnosis codes	All obstetrics patients		Maternity patients	
Pre-eclampsia and eclampsia	O14.0-O15.9	14,335	1.51%	9,124	2.05%
Haemorrhage	O2O.8 O20.9 O44.1 O46 O67 O72 O03-6.1&6	74,946	7.88%	42,220	9.51%
Diabetes	O24 R81 E1	17,995	1.89%	9,395	2.12%
Infection	O23 O44.1 O75.3 O86 R50 J22.X O03-6.0&5	27,258	2.87%	8,709	1.96%
Hypertension	O16 O11 I10	28,089	2.95%	8,551	1.93%
Obesity	E66	2,002	0.21%	947	0.21%
Smoker	Z72.0	19,597	2.06%	14,142	3.18%
Lifestyle risk factors	Z72.1 Z72.2 Z72.4&8&9 Z35.7 Z86.4 Z91.5 Z86.5	9,568	1.01%	6,406	1.44%
Abortion	O01 O02 O03 O04 O05 O06 O07 O08	7,408	0.78%	407	0.09%
Allergy	Z88	15,041	1.58%	10,150	2.29%
Past history of disease	Z85 Z86.0&1&2&3&6&7 Z87.4	8,556	0.90%	5,777	1.30%
Complications in past pregnancy	Z87.5 Z87.6	2,785	0.29%	1,804	0.41%
Perineal laceration	O70.2 O70.3	93,873	9.87%	93,386	21.03%

Table 3 Descriptive statistics

	All obstetrics patients		Obstetrics patients - trimmed sample		Obstetrics patients - long stay sample		All maternity patients	
	mean	Std_dev	mean	Std_dev	mean	Std_dev	mean	Std_dev
Cost	1088	849	1025	726	1538	1368	1578	915
Age	28.09	6.92	28.07	6.96	28.25	6.63	28.82	6.42
Income index	0.177	0.134	0.176	0.134	0.182	0.136	0.170	0.132
# babies	0.405	0.509	0.399	0.507	0.453	0.523	0.840	0.416
Birth weight (1000g)	1.174	1.630	1.165	1.633	1.232	1.604	2.432	1.562
Delivered dead	0.002	0.043	0.002	0.043	0.002	0.045	0.004	0.060
# operations	1.120	1.429	1.079	1.398	1.412	1.604	2.348	1.212
# diagnoses	2.294	1.432	2.256	1.409	2.563	1.556	3.165	1.411
Pre/eclampsia	0.015	0.122	0.011	0.105	0.043	0.202	0.021	0.142
Haemorrhage	0.079	0.270	0.074	0.262	0.116	0.320	0.096	0.294
Diabetes	0.019	0.136	0.018	0.132	0.028	0.164	0.021	0.144
Infection	0.029	0.167	0.023	0.151	0.066	0.249	0.019	0.138
Hypertension	0.030	0.169	0.029	0.167	0.035	0.184	0.019	0.137
Obesity	0.002	0.046	0.002	0.046	0.002	0.040	0.002	0.046
Smoker	0.021	0.142	0.021	0.142	0.021	0.144	0.032	0.175
Lifestyle risk factors	0.010	0.100	0.010	0.097	0.013	0.115	0.014	0.119
Abortion	0.008	0.088	0.007	0.086	0.010	0.100	0.001	0.030
Allergy	0.016	0.125	0.016	0.124	0.017	0.129	0.023	0.149
Past disease	0.009	0.094	0.009	0.093	0.011	0.105	0.013	0.113
Comps in past pregnancy	0.003	0.054	0.003	0.054	0.003	0.050	0.004	0.064
Perineal laceration	0.099	0.298	0.092	0.289	0.148	0.355	0.210	0.407
Observations	952,273		834,847		117,426		445,339	

Note that these fixed effects are not equivalent to the efficiency estimates derived from applying cross-sectional stochastic frontier models, for which a second-stage analysis is inappropriate. This is because stochastic frontier models rely on estimation of an efficiency frontier in relation to which each organisation's efficiency is measured. This means that efficiency estimates are not independent observations, thereby invalidating the standard assumptions for regression analysis (Simar and Wilson, 2004). Instead, we avoid estimating a frontier and exploit the multi-level structure of our data to extract independently distributed departmental fixed effects

While differential efficiency (or effort) is unobservable, observable factors driving residual variation in costs across departments can be explored. To this end, the departmental fixed effects estimated in the first stage are regressed against a set of departmental variables in a second stage regression of the form:

$$\hat{u}_j = \delta_0 + \delta_1 z_j + \boldsymbol{\delta}'_x \mathbf{x}_j + \upsilon_j \qquad (2)$$

where $\mathbf{x}_j$ is a vector of variables capturing departmental characteristics, summarised in Table 4. This includes the number of patients treated, insurance contributions per birth[3] and the number of staff employed.[4] We also include variables describing the hospital in which the department is located, including whether it has a teaching function, a neonatology department operating alongside the obstetric department as a distinct unit, and how many sites the obstetrics department is split over, if any. We also consider the quality of clinical coding by measuring what proportion of the hospital's total caseload cannot be apportioned to any HRG.

Table 4 Departmental descriptive statistics

	mean	**Std_dev**
Number of patients (100s)	70.02	41.03
Insurance per birth (£)	545.15	17.08
Staff	99.64	48.39
Teaching status	0.15	0.36
Neonatology dept	0.51	0.50
Total sites	1.15	0.50
Coding quality (%)	1.18	1.97
Input price index (x100)	112.40	8.60
Departments	136	

Arguably all the variables included in $\mathbf{x}_j$ are within the control of the department, if only in the short run. Hospitals have (at least some) discretion about their scale of operation, their staffing complements, and the hospital's configuration. They are also able to influence their insurance contributions to some extent by improving their risk management strategies. While these variables might explain variation in costs, they do not represent differing exogenous or environmental cost constraints and, as such, it would not be legitimate to control for these factors in a performance analysis.

However, English hospitals have limited ability to control some of their costs. The fundamental reason is that they cannot locate where they wish – public hospitals are charged with serving their

[3] Insurance contributions form a significant proportion of costs incurred in obstetrics departments (http://www.timesonline.co.uk/tol/life_and_style/health/article5168353.ece accessed 17/11/08). Each department's contribution is based on staffing levels, number of births, claims history and risk management strategies (Fothergill, personal communication)
http://www.nhsla.com/NR/rdonlyres/8A429D32-B5F2-41CE-A60F-087775DA28DC/0/NHSLAFactsheet5200506.xls
accessed 11/11/08

[4] We measure the number of whole time equivalent obstetricians, gynaecologists and midwives per 100 patients, as reported to the NHS Litigation Authority. This index weighs staff of different types according to their respective wages.
http://www.ic.nhs.uk/webfiles/publications/esr_earnings_2007-7/July%202007%20Earnings%20Estimates%20Tables.pdf
accessed 27/11/08

local population and they cannot simply chose to relocate to another part of the country where circumstances may be more favourable. In effect, hospitals face locational constraints that impact on their production costs and that are outside their control. In equation (2) these constraints are captured by the variable z_j that captures differences in the labour and capital factor prices faced by providers in different parts of England as measured by an input price index (the so-called Market Forces Factor (MFF)) (Mason et al., 2009).

In order to provide a picture of the obstetrics departments' relative performance, we estimate the variation in their average costs after controlling for their patient characteristics and exogenous factor prices. This can be easily achieved by indirect standardization techniques:

$$\hat{u}_j^{is} = \hat{u}_j - \hat{u}_j^z \quad (3)$$

$$\hat{u}_j^z = \hat{\delta}_0 + \hat{\delta}_1 z_j + \hat{\boldsymbol{\delta}}'_x \overline{\mathbf{x}}_j \quad (4)$$

where $\hat{u}_j$ is obtained from equation (1) and $\overline{\mathbf{x}}_{jx}$ is the vector of variables in equation (2) set to their mean. These variable are not used for standardization but, instead, are included in order to avoid omitted variable problem that arises if factor prices, z_j, are correlated with $\mathbf{x}_j$ (O'Donnell et al., 2008). Finally, $\hat{\delta}_1$ and $\hat{\boldsymbol{\delta}}'_x$ are parameters estimated from equation (2).

We interpret $\hat{u}_j^{is}$ as a measure of relative departmental performance in controlling costs, purged of the effect of the factor prices they face and the characteristics of their patients.

The two stage model described here is based on two main assumptions about the data generating process (DGP) that determines the observed cost, input, case-mix and environmental variables in the obstetrics departments. First, our model assumes a separability condition between environmental factors, case-mix and the inputs in the cost function of the obstetrics departments. This allows us to purge the influence of case-mix and factor prices from the departmental average cost. This is similar to the assumption proposed in Simar and Wilson on the DGP that describes the relationship between production function, environmental factors and efficiency (Simar and Wilson, 2004).

Second, we assume that the obstetrics departments share the same cost function. This allows us to describe how departmental level variables influence department costs in the second stage and is required in order to identify what factors are responsible for the variation in average costs across departments. This assumption is generally unrealistic for analysis at hospital level given the multiproduct nature of hospital activity. But we argue that the activity of hospital departments, such as obstetrics, is more homogeneous and, consequently, can be realistically considered as determined by the same underling production process.

The two-stage model we have specified borrows from the literature on EDV models that are widely applied in political analysis studies. Jusko and Shively and Lewis and Linzer discuss extensively the hypothesis under which EDV models involving a two stage approach are consistent and efficient (Jusko and Shively, 2005, Lewis and Linzer, 2005). In particular, heteroscedastic sampling errors in the estimated dependent variables might result in biased standard errors in the second stage analysis. Efron robust SE estimators are adopted, which are known to provide a suitable solution under this hypothesis[5].

Note also that the potential gains in efficiency from estimating a two-stage model in a single stage are modest when considerable information is available at the bottom level (Lewis and Linzer, 2005). In our study we have almost one million observations at patient level, with each department having no less than one thousand observations. This makes our two-stage procedure a valid approach to the analysis.

[5] While the Breush-Pagan test for test for heteroshedasticity is negative in the second stage model (equation 2) this is known to be not completely reliable in small samples (Long and Ervin, 2005). Therefore, we elect to apply Efron standard errors.

4. Results

4.1 Patient-level costs

Estimation results are presented in Table 5. Results for the full sample of obstetrics patients appear first, with the model explaining 55% of the variation in patient costs (R-sq overall=0.5514). The first set of variables show the estimated cost for each HRG relative to the cost of a normal delivery, after conditioning on the other covariates. For maternity HRGs the estimates are little different to the mean costs (compared to a normal delivery) reported in Table 1. Most of the neonatal HRGs are not statistically significant, reflecting the relatively low number of observations in these HRGs. The main reason is that neonatal care, particularly for more complex patients, is mainly managed by neonatology departments.

Estimates from the full sample show that costs are driven by patients characteristics over and above their HRG classification. In particular, pre-eclampsia/eclampsia and infections explain an economically relevant portion of the average cost of patients treated in obstetrics. Other important health conditions associated with high cost are diabetes and total number of diagnosis and operations performed. Interestingly, the socioeconomic status of the patients is associated with higher costs, a finding in line with evidence about the relationship between socioeconomic deprivation of the patient treated and the cost of treatment (Cookson and Laudicella, 2009). Conversely some patient conditions are associated with lower costs, the most economically relevant being the occurrence of abortion.

Results derived from estimating the equation on the trimmed and long stay samples are then presented. For the trimmed sample, the patient's HRG is the most important predictor of variation in costs while additional patient characteristics are generally not significant. An exception is patients that underwent an abortion who typically have lower costs. In contrast, it appears that patients who stay beyond their HRG trimpoint do so for good reason, with many of the diagnostic characteristics over and above their HRG being significant explanators of cost both statistically and economically. This finding supports the use of extra payments for patients who stay beyond the trimpoint as it suggests that the HRG alone is not sufficient to account for cost variations among long-stay patients.

The final set of estimates in Table 5 presents results when considering maternity patients only (i.e., patients assigned to HRGs N06-N11). Results are broadly similar to those for all obstetrics patients, unsurprisingly given that maternity patients comprise 47% of the total. But there are some notable differences. The baby's weight and mother's smoking behaviour are associated with lower costs. The former is an indicator of baby and mother's health, while the latter reflects the circumstance that mothers in better health are less likely to quit smoking during pregnancy, as shown in the economic literature (Rosenzweig and Schultz, 1983). Finally, it is notable that the occurrence of an infection is by far the most relevant determinant of high costs in maternity care, patients suffering infections costing £300 more to care for than those who do not. Table 3 shows that 2% of maternity patients are at risk of infections. Particularly if contracted after admission, investment in efforts to reduce the risk of infection might generate substantial cost savings.

4.2 Estimation and comparison of department effects

The primary purpose of the patient-level equations is to control for a broad range of patient characteristics when assessing variation in average costs across obstetrics departments. After taking these patient characteristics into account, there remains a high degree of unexplained variation in the average cost per patient across departments, as indicated by the value of *rho* in Table 5. When considering all obstetrics patients, 19% of the variation in costs is explained at department level rather than due to observed characteristics of the patients within departments. For patients discharged before the trimpoint, there is a high proportion of variance in costs between departments (*rho*=42%). Departmental variance in costs is less evident when considering those with longer lengths of stay (*rho*=8%). This is largely due to the greater variation in costs for patients who stay beyond the trimpoints, for whom we are able to attribute *per diem* estimates of the long-stay costs.

Table 5 First stage estimates

	All obstetrics patients			Obstetrics patients - trimmed sample			Obstetrics patients - long stay sample			All maternity patients		
	coeff	se	t	coeff	se	t	coeff	se	t	coeff	se	t
Neonates - Died <2 days old	-279.19	107.21	-2.60	-254.59	108.19	-2.35	(dropped)					
Neonates with Multiple Minor Diagnoses	237.34	116.17	2.04	328.25	108.01	3.04	-66.01	47.83	-1.38			
Neonates with one Minor Diagnosis	-184.02	100.08	-1.84	-105.17	83.86	-1.25	-414.22	212.30	-1.95			
Neonates with Multiple Major Diagnoses	-186.20	419.53	-0.44	39.48	394.64	0.10	(dropped)					
Neonates with one Major Diagnosis	-215.25	219.76	-0.98	-60.47	184.70	-0.33	(dropped)					
Normal Delivery w cc	681.00	72.74	9.36	784.68	74.30	10.56	1627.34	97.23	16.74	636.67	64.38	9.89
Assisted Delivery w cc	1023.30	59.96	17.07	1173.00	64.19	18.27	1959.98	137.48	14.26	990.87	51.82	19.12
Assisted Delivery w/o cc	308.75	19.09	16.18	424.30	19.38	21.89	624.24	40.83	15.29	316.33	18.91	16.73
Caesarean Section w cc	2119.47	74.40	28.49	2201.20	74.44	29.57	3567.02	108.67	32.83	2070.30	75.21	27.53
Caesarean Section w/o cc	1192.64	52.35	22.78	1253.90	52.22	24.01	1883.36	68.02	27.69	1191.64	52.11	22.87
Antenatal Admissions	-303.82	38.92	-7.81	-321.03	37.82	-8.49	-360.25	39.30	-9.17			
General Abdominal Disorders <70 w/o cc	-170.30	72.90	-2.34	-123.76	70.50	-1.76	-93.26	257.91	-0.36			
Examination, Follow up and Special Screening	-338.14	58.46	-5.78	-324.99	56.24	-5.78	-490.77	65.43	-7.50			
Upper Genital Tract Minor Procedures	87.37	112.01	0.78	130.91	123.78	1.06	-193.13	103.68	-1.86			
Medical Termination of Pregnancy	-56.83	42.94	-1.32	-7.55	36.90	-0.20	-235.39	89.09	-2.64			
Treatment of Fibroids, Menstrual Disorders, or Endometriosis	-253.08	49.81	-5.08	-226.43	47.14	-4.80	503.12	583.88	0.86			
All other HRGs	-1.75	59.06	-0.03	31.29	60.17	0.52	646.17	144.14	4.48			
Age	-1.31	1.24	-1.05	1.02	1.36	0.75	-3.64	3.04	-1.20	-3.43	1.66	-2.06
Age^2	0.04	0.02	1.93	-0.02	0.02	-0.63	0.15	0.06	2.70	0.08	0.03	2.66
Income index	36.18	8.56	4.23	14.14	5.88	2.41	12.24	32.43	0.38	33.47	10.51	3.19
# babies	72.98	36.35	2.01	-14.05	32.93	-0.43	148.49	45.98	3.23	119.90	20.88	5.74
Birth weight	-14.37	12.56	-1.14	17.77	11.77	1.51	-69.54	17.39	-4.00	-53.76	5.29	-10.17
Delivered dead	-26.71	52.67	-0.51	-11.16	45.66	-0.24	41.48	104.76	0.40	-55.07	36.06	-1.53
# operations	34.87	7.72	4.52	19.81	8.06	2.46	-4.68	7.28	-0.64	19.07	3.92	4.87
# diagnoses	24.69	5.57	4.43	-0.98	5.57	-0.18	50.68	6.60	7.68	22.61	3.20	7.07
Pre/eclampsia	299.40	20.94	14.30	2.61	9.84	0.26	308.23	31.87	9.67	359.27	26.60	13.50
Haemorrhage	21.25	12.88	1.65	-22.62	12.71	-1.78	39.01	14.82	2.63	51.25	15.06	3.40
Diabetes	51.40	14.45	3.56	4.07	19.01	0.21	72.89	24.44	2.98	75.98	13.08	5.81
Infection	185.45	16.59	11.18	11.56	9.41	1.23	253.97	25.09	10.12	303.26	27.67	10.96
Hypertension	17.24	13.97	1.23	-18.72	12.84	-1.46	31.35	30.58	1.03	40.66	26.58	1.53
Obesity	-56.16	29.90	-1.88	-3.27	26.59	-0.12	-1.61	107.74	-0.01	7.83	36.27	0.22
Smoker	15.62	24.12	0.65	36.51	23.06	1.58	73.22	38.77	1.89	-38.71	10.12	-3.82
Lifestyle risk factors	-16.86	25.78	-0.65	-31.56	25.08	-1.26	58.65	35.89	1.63	21.06	11.79	1.79
Abortion	-160.11	36.25	-4.42	-210.61	32.89	-6.40	-135.99	65.29	-2.08	64.45	38.04	1.69
Allergy	-51.23	14.02	-3.65	-12.38	13.37	-0.93	-112.54	24.79	-4.54	-33.41	6.67	-5.01
Past disease	-15.46	12.80	-1.21	-11.92	10.42	-1.14	-13.37	32.59	-0.41	-4.55	8.37	-0.54
Comps in past pregnancy	-62.98	33.37	-1.89	-30.91	36.31	-0.85	-54.90	60.07	-0.91	-37.10	22.05	-1.68
Perineal laceration	-41.06	8.39	-4.89	-12.91	8.38	-1.54	-105.49	10.99	-9.60	-30.64	5.64	-5.43
Constant	917.46	36.50	25.13	901.48	37.70	23.91	1388.56	55.44	25.05	1077.45	31.23	34.50
Sigma_u	250.31			237.58			346.27			362.03		
Sigma_e	524.21			278.82			1127.89			573.82		
Rho	0.1857			0.4206			0.0861			0.2847		
R-sq within	0.5675			0.8246			0.2821			0.5444		
R-sq between	0.5161			0.5446			0.0855			0.0558		
R-sq overall	0.5514			0.7694			0.2693			0.4739		
Patients	952,273			834,847			117,426			445,339		
Departments	136			136			136			136		

In our second stage analysis, we consider what influence departmental characteristics has over variance in $\hat{u}_j$. The fixed effects from estimating equation (1) for all obstetrics patients are highly correlated with those from the trimmed sample (r=0.98) while the correlation is lower when compared to fixed effects from the long-stay and maternity samples (r=0.83 and r=0.87 respectively).

Table 6 reports results from the model in equation (2) according to the sample of patients considered. There is some evidence of lower costs in obstetrics departments with higher volumes of activity, although this effect is not statistically significant when considering any of the sub-samples of patients. Costs are also lower in the obstetrics department if the hospital has a separate neonatology unit, probably because more expensive neonatal care can be delivered there instead of in the obstetrics department. Finally, higher average costs are evident in departments that face higher input prices, although the effect is not significant in the maternity sample. No other variables are significant explanators of the variation in departmental costs.

After controlling for differences among departments in the type of patients they treat and in the factor prices they face by applying equation (3), we rank departments according to their average costs and report the 95% confidence intervals around their mean. Figure 3 shows that departmental ordering is similar if the analysis is based on the full sample of obstetrics patients or limited to only those patients discharged before the trimpoint. This is due to the fact that the patients included in the latter sample represent 88% of the full sample. The ordering is more sensitive to whether analysis is restricted to long-stay patients (Figure 4) or maternity patients (Figure 5). However, re-ranking occurs mainly in the middle of the distribution. At the extremes, identification of those departments with the lowest and highest costs is not sensitive to what sample of patients is considered.

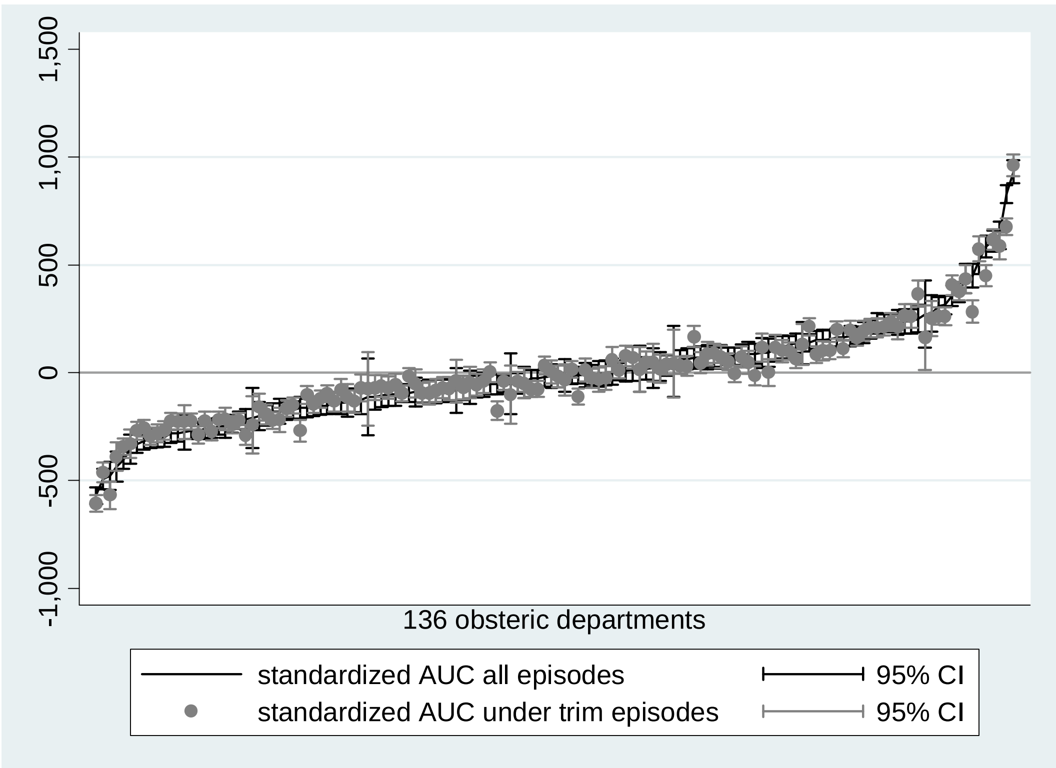

Figure 3 Departmental rankings from analysis of all obstetrics patients and trimmed sample

Table 6 Results of second stage estimates

	All obstetrics patients			Obstetrics patients - trimmed sample			Obstetrics patients - long stay sample			All maternity patients		
	coeff	se	t	coeff	se	t	coeff	se	t	coeff	se	t
Number of patients (000s)	-1.58	0.66	-2.39	-1.21	0.63	-1.93	-1.65	1.03	-1.60	-1.75	1.17	-1.50
Insurance per birth (£)	0.83	1.32	0.63	1.01	1.33	0.76	0.37	1.50	0.25	1.81	2.01	0.90
Staff	0.72	0.44	1.64	0.62	0.42	1.49	0.68	0.69	0.98	1.31	0.88	1.48
Teaching status	-65.54	53.77	-1.22	-90.65	52.04	-1.74	-7.35	73.46	-0.10	-5.69	97.65	-0.06
Neonatology dept	-111.23	42.71	-2.60	-99.51	40.44	-2.46	-158.55	63.05	-2.51	-160.57	64.70	-2.48
Total sites	50.64	46.88	1.08	42.65	41.32	1.03	86.24	92.39	0.93	37.60	53.63	0.70
Coding quality	-3.50	9.95	-0.35	-2.49	9.43	-0.26	-17.37	14.66	-1.19	-1.68	16.58	-0.10
Input price index (x100)	7.03	2.71	2.59	6.32	2.53	2.50	9.39	4.23	2.22	5.49	4.57	1.20
Constant	-1153.94	815.46	-1.42	-1186.50	809.43	-1.47	-1208.04	1071.64	-1.13	-1564.25	1304.47	-1.20
R-sq	0.19			0.17			0.17			0.11		
Departments	136			136			136			136		

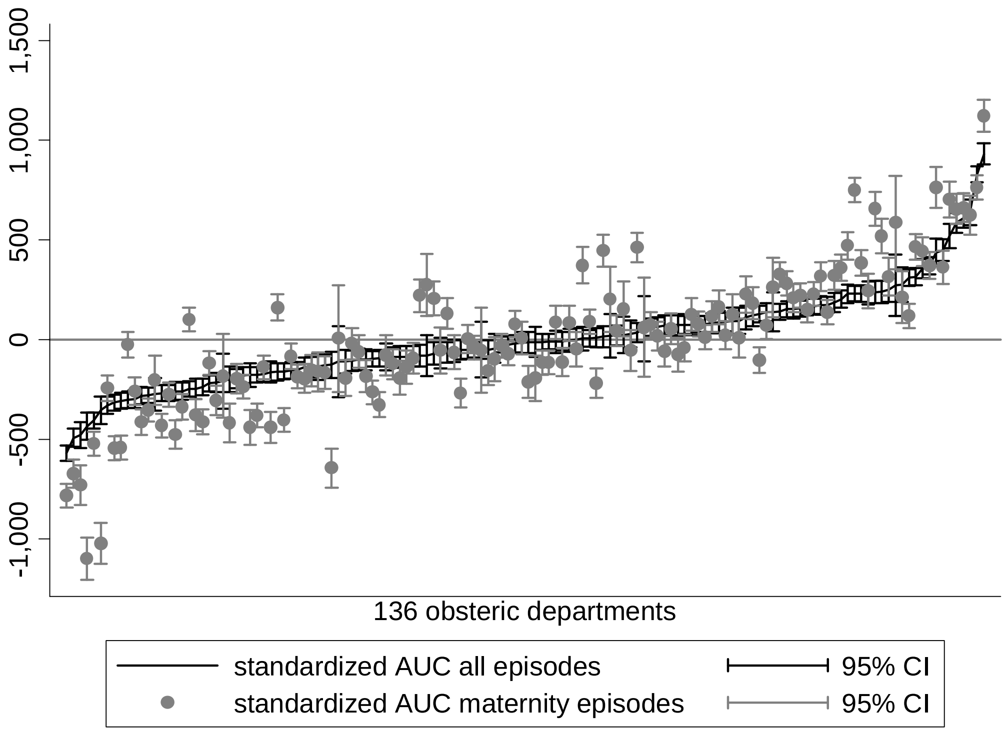

Figure 4 Departmental rankings from analysis of all obstetrics patients and long-stay sample

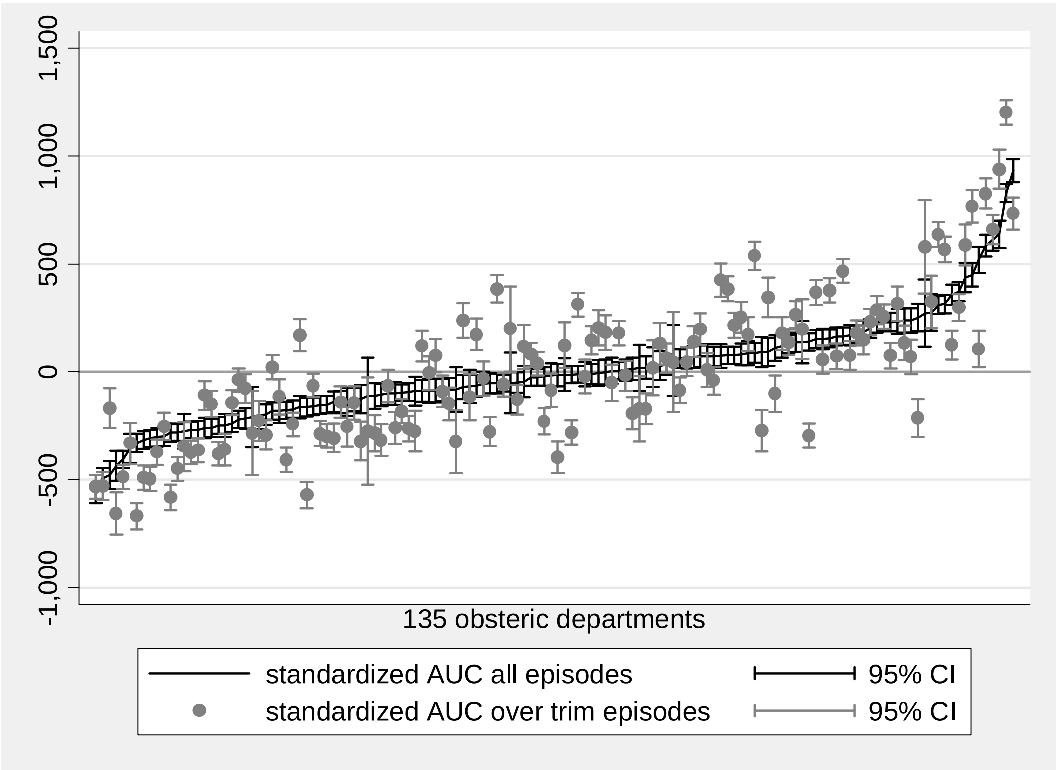

Figure 5 Departmental rankings from analysis of all obstetrics patients and maternity patients

5. Conclusions

By using patient-level data our analysis offers several contributions over other approaches to consideration of hospital costs or efficiency. The first advantage is that the researcher is not restricted to consideration of the hospital as the unit of analysis but can undertake specialty-level analysis. The latter are often more homogeneous units that can be assumed to be subject to a common production function. One of the main analytical problems with analysing hospitals is that each comprises a diverse range of specialties and any failure to account for the heterogeneous mixture of production functions within and across hospitals will undermine the comparative exercise.

Second, we provide more insight into why costs vary from one patient to another, since we are able to account for a much broader range of patient characteristics than simply the HRG to which the patient is allocated. As would be expected, the patient’s HRG is the most significant explanatory variable but diagnostic markers over and above the HRG, are significant. Perhaps of most interest is that patients suffering an infection have substantially higher costs. These costs might be avoided if the risk of infection could be reduced.

Diagnostic characteristics are particularly important in explaining the variation in cost, particularly among long-stay and maternity patients. Our finding provides support for the policy of extra-payments for length of stay outliers (Department of Health, 2009) as well as for policy enlarging the varieties of HRGs available. The new version 4 HRGs, which have recently been developed, may be more successful at capturing variation in costs among maternity patients, for example. Compared to the version 3.5 HRGs used in this study, the number of maternity HRGs in version 4 has expanded from six to nine and an age split (at 18 years) has been introduced.

Third, the multilevel structure of patient-level data enables us to obtain a departmental fixed effect without resorting to stochastic frontier methods under a cross-sectional framework. Thus, we are not forced to make assumptions about the production or cost frontier and are able to investigate variations in our fixed effects in a second-stage analysis – a process that would be suspect if analysing variation in non-independently distributed efficiency estimates (Wang and Schmidt, 2002, Simar and Wilson, 2004). We control for the diverse characteristics of each department’s patients by washing out this important influence on costs, then we provide a second-stage analysis of departmental fixed effects. After taking account of these patient characteristics, substantial variation in the average cost per patient persists across departments. Higher average costs are evident in smaller obstetrics departments, those in hospitals that lack a separate neonatology department and where factor prices (as measured by MFF) are higher. The fact that insurance contributions are not significant in explaining variations in costs among departments is reassuring, as it suggests that the burden of these premiums is similar across departments.

Obstetric departments are ranked according to their average costs purged of heterogeneity in patient characteristics and factor prices. The relative rank of most departments varies according to the subsample of patients considered: all obstetrics patients, patients discharged prior to the trimpoint or long-stay patients, and maternity patients. At the extremes of the distribution, though, the relative position of the lowest and highest cost departments remains unchanged.

Although we have controlled for an extensive set of patient characteristics and differences in factor prices in our analysis, there may be further explanations as to why costs vary across departments that our analysis has been unable to account for. One possibility is that hospitals differ in their coding practice, to the extent that some provide better coded HES data than others. Our variable measuring coding quality was not significant however. Another possibility is that hospitals assess their costs in different ways, with differences likely to stem from how they have decided to apportion shared resources, such as doctors working across specialties, or hospital overheads, even though the Department of Health give detailed guidelines on common accountancy practice to be adopted. While this apportionment is problematic whatever costing system is in place (Jackson, 2001), it may have less impact in obstetrics departments, these being relatively self-contained, than for specialties that are more inter-linked with others. A further reason why costs might differ, of course, is that some obstetrics are simply better organised and more efficient than others. Ultimately determining the remaining reasons why some obstetrics departments have such high costs is properly the responsibility of hospital management and our analysis identifies those obstetrics departments where managerial effort is most required.

Appendix 1: Starting and analytical samples

We apply standard criteria to identify duplicate records in HES (Castelli et al., 2008). This provides us with a starting sample of 1,009,747 FCEs. As Table A1 shows, a number of records were dropped from the analysis for the following reasons.

- We omit eight hospitals where fewer than 1,000 FCEs are recorded in the obstetrics department.[6] 1,125 FCEs are dropped because of this.
- Two hospitals did not use the obstetrics specialty code when making their Reference Cost returns, making it impossible to match their HES and cost data. Three other hospitals failed to report costs for a high proportion of the HRGs to which their patients were allocated. These five hospitals are excluded, meaning that 30,895 patients are dropped from the analysis.[7]
- For 13,063 patients, there was no corresponding reference cost reported by the patient's hospital for the HRG to which they were allocated, meaning that a cost could not be assigned to them. These losses were not at random being concentrated among a selective set of hospitals.[8]
- FCEs assigned to "U" HRG codes are dropped, of which there were 12,014.
- A small number of obstetrics patients are recorded as having invalid or very long lengths of stay. Some of these values may be due to errors in recording either the date of admission or date of discharge, although some may be genuine values. Conservatively we have decided to drop patients with a length of stay of more 100 days. This means dropping 133 records.
- Finally, we exclude 260 observations with a cost in excess of £15,000.

Table A1 Starting and analytical samples		
	observations	%
Starting sample	1,009,747	100.00%
Drop activity in low volume NHS hospitals	1,125	0.1%
Drop hospitals that did not assign obstetrics specialty code in their Reference Cost return or that had low volumes after matching	30,875	3.1%
Drop activity where that could not be matched to Reference Cost data	13,063	1.3%
Drop activity assigned to U code HRGs	12,014	1.2%
Drop FCEs with LoS more than 100 days	133	0.0%
Drop FCEs with cost more than £25,000	260	0.0%
Sample for analysis	951,277	94.3%

[6] RC1 Bedford Hospital NHS Trust (18 FCEs), RD1 Royal United Hospital Bath NHS Trust (50), RDZ The Royal Bournemouth And Christchurch Hospitals NHS Foundation Trust (9), RG3 Bromley Hospitals NHS Trust (97), RLN City Hospitals Sunderland NHS Foundation Trust (547), RN7 Dartford And Gravesham NHS Trust (124), RNH Newham University Hospital NHS Trust (277), RXW Shrewsbury And Telford Hospital NHS Trust (3)

[7] RG2 Queen Elizabeth Hospital NHS Trust (11,676 FCEs), RJ1 Guy's And St Thomas' NHS Foundation Trust (5,354), RAJ Southend University Hospital NHS Foundation Trust (10,590). RBZ Northern Devon Healthcare NHS Trust (1,297), RNJ Barts And The London NHS Trust (1,998).

[8] Some departments have a minimal number of obstetrics patients assigned to a diverse range of HRGs. Examples are RGQ Ipswich Hospital NHS Trust (where 1,214 FCEs are allocated to 27 HRGs for which costs are not reported); RQM Chelsea And Westminster Hospital NHS Foundation Trust (849 FCEs, 63 HRGs).

Appendix 2: Assigning reference costs to individual HES records

To assess the costs of patient care we use the Reference Cost database, which is a unique international resource. England is unusual in having made it mandatory for all NHS hospitals to report costs for the patients they treat. In no other country are disaggregated cost data routinely available for all providers, even where hospitals are paid on the basis of their activity (Schreyögg et al., 2006). This means that analysis of hospital costs in other countries is always based on either a limited sample of hospitals or utilises data reported at hospital level, such as total expenditure. In England, the Reference Costs form the basis for calculating the national tariff, according to which hospitals are paid under Payment by Results (PbR). To our knowledge, no research has exploited the original data provided by each hospital (although work has been based on cost data aggregated to HRGs or by hospital).

Hospitals in England do not collect detailed information on each patient's resource use that would allow bottom-up costing of patient care. Rather, every hospital applies a standard top-down costing methodology to produce a Reference Cost for each elective, day case and non-elective HRG in each specialty. This means that total hospital costs are progressively cascaded down first to treatment services (wards, theatres, pharmacy, etc), then to specialties, and finally to HRGs. Reference Costs are calculated on a full absorption basis, meaning that they should reflect the full and true cost of the service delivered (Department of Health, 2008).

In making their Reference Cost returns hospitals report five pieces of cost information for each HRG (*h*) in each of their specialties. So, for any given obstetrics department, *j*, the following will be reported:

- Average cost per day case in HRG *h*: c_{hj}^{d}
- Average cost for elective patients in HRG *h* with a length of stay below HRG-specific trimpoint value: c_{hj}^{e}
- Excess *per diem* cost for an elective patient in HRG *h* who stays in hospital beyond the HRG-specific trimpoint: ex_{hj}^{e}
- Average cost for non-elective patients in HRG *h* with a length of stay below HRG-specific trimpoint value: c_{hj}^{n}
- Excess *per diem* cost for a non-elective patient in HRG *h* who stays in hospital beyond the HRG-specific trimpoint ex_{hj}^{n}

Trimpoints are defined for length of stay outliers in each HRG according to whether the patient was admitted as an elective or non-elective. We define t_h^e as the elective trimpoint in days and t_h^n as the nonelective trimpoint for HRG *h*.[9]

The Reference Cost information provided by each hospital is assigned to each patient record in HES, according to the type of admission and how long each patient stays in hospital, as follows:

- If the patient was treated as a day case $if \quad a_{ihj}^{d} \rightarrow c_{hj}^{d}$
- If the patient was an elective with length of stay at or below the elective trimpoint $if\,(a_{ihj}^{e}, L_{ihj} \leq t_h^e) \rightarrow c_{hj}^{e}$
- If the patient was an elective with length of stay above the elective trimpoint $if\,(a_{ihj}^{e}, L_{ihj} > t_h^e) \rightarrow c_{hj}^{e} + \left[ex_{hj}^{e} \times (L_{ihj} - t_h^e)\right]$

[9] Trimpoints are revised periodically by the Information Centre. We have applied the trimpoints that were published alongside the national tariff for 2005/6
http://www.dh.gov.uk/en/Publicationsandstatistics/Publications/PublicationsPolicyAndGuidance/DH_4091529 accessed 15/9/08

- If the patient was non-elective (including maternity, baby or a transfer) with length of stay at or below the non-elective trimpoint $if\,(a_{ihj}^{n}, L_{ihj} \leq t_{h}) \rightarrow c_{hj}^{n}$
- If the patient was a non-elective (including maternity baby or a transfer) with length of stay above the non-elective trimpoint $if\,(a_{ihj}^{e}, L_{ihj} > t_{h}^{n}) \rightarrow c_{hj}^{n} + \left[ex_{hj}^{n} \times (L_{ihj} - t_{h}^{n}) \right]$

References

Bhalotra, S. & Zamora, B. (2008) Achieving the millennium development goal for primary schooling in India; in McGillivray, M. (ed.) *Achieving the Millennium Development Goals* Basingstoke, Hampshire, Palgrave Macmillan.

Bilodeau, D. Crémieux, P.Y. & Ouellette, P. (2000) Hospital cost function in a non-market health care system. *Review of Economics and Statistics,* 82**,** 489-498.

Castelli, A., Laudicella, M. & Street, A. (2008) *Measuring NHS output growth,* York, Centre for Health Economic research paper 43.

Cookson, R. & Laudicella, M. (2009) *Do the poor still cost more? The relationship between small area income deprivation and length of stay for elective hip replacement in the English NHS from 2001/2 to 2006/7, HEDGg working paper 09/07.,* York, University of York.

Department of Health (2008) NHS *costing manual 2007/08,* London, Department of Health.

Department of Health (2009) *Payment by Results Guidance for 2009-10,* Leeds, Department of Health.

Harper, J., Hauck, K. & Street, A. (2001) Analysis of costs and efficiency in general surgery specialties in the United Kingdom. *European Journal of Health Economics,* 2**,** 150-157.

Hauck, K., Rice, N. & Smith, P.C. (2003) The influence of health care organisations on indicators of health system performance. *Journal of Health Services Research and Policy,* 8**,** 68-74.

Hauck, K. & Street, A. (2006) Performance assessment in the context of multiple objectives: a multivariate multilevel approach. *Journal of Health Economics*.

Hollingsworth, B. (2008) The measurement of efficiency and productivity of health care delivery. *Health Economics,* 17**,** 1107-1128.

Jackson, T. (2001) Using computerised patient-level costing data for setting drg weights: the Victorian (Australia) cost weights studies. *Health Policy,* 56**,** 149-163.

Jacobs, R., Smith, P.C. & Street, A. (2006) *Measuring efficiency in health care: analytical techniques and health policy,* Cambridge, Cambridge University Press.

Jusko, K. L. & Shively, W. P. (2005) Applying a two-step strategy to the analysis of cross-national public opinion data. *Political Analysis,* 13**,** 327-344.

Lewis, J. B. & Linzer, D. A. (2005) Estimating regression models in which the dependent variable is a constant. *Political Analysis,* 13**,** 345-364.

Manning, W. G. (1998) The logged dependent variable, heteroscedasticity, and the retransformation problem. *Journal of Health Economics,* 17**,** 283-295.

Mason, A., Street, A., Miraldo, M. & Siciliani, L. (2009) Should prospective payments be differentiated for public and private healthcare providers? *Health Economics Policy and Law*.

O'Donnell, O., van Doorslaer, E., Wagstaff, A. & Lindelow, M. (2008) *Analysing health equity using household survey data.* Washington DC, World Bank Publications.

Olsen, K.R. & Street, A. (2008) The analysis of efficiency among a small number of organisations: how inferences can be improved by exploiting patient-level data. *Health Economics,* 17**,** 671-281.

Rosenzweig, M.R. & Schultz, T.P. (1983) Estimating a household production function: heterogeneity, the demand for health inputs, and their effects on birth weight. *Journal of Political Economy,* 91**,** 723-746.

Rosko, M.D. & Mutter, R.L. (2008) Stochastic frontier analysis of hospital inefficiency. *Medical Care Research and Review,* 65**,** 131-166.

Schreyögg, J. Stargardt, T. Tiemann, O. & Busse, R. (2006) Methods to determine reimbursement rates for diagnosis related groups (drg): a comparison of nine european countries. *Health Care Management Science,* 9**,** 215-223.

Simar, L. & Wilson, P.W. (2004) Estimation and inference in two-stage, semi-parametric models of production processes. *Discussion Paper no. 0307.* Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve: Belgium.

Wang, H. J. & Schmidt, P.C. (2002) One-step and wo-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis,* 18**,** 129-144.

Worthington, A.C. (2004) Frontier Efficiency measurement in health care: a review of empricial techniques and selected applications. *Medical Care Research and Review,* 61**,** 135-169.