



## How much should be paid for specialised treatment?

Silvio Daidone\*, Andrew Street<sup>1</sup>

Centre for Health Economics, University of York, Heslington, York, YO10 5DD, UK

### ARTICLE INFO

Article history:  
Available online 14 February 2013

Keywords:  
England  
Hospital specialisation  
Prospective payment systems  
Diagnosis related groups  
Healthcare resource groups  
Treatment costs

### ABSTRACT

English health policy has moved towards establishing specialist multi-disciplinary teams to care for patients suffering rare or particularly complex conditions. But the healthcare resource groups (HRGs), which form the basis of the prospective payment system for hospitals, do not explicitly account for specialist treatment. There is a risk, then, that hospitals in which specialist teams are based might be financially disadvantaged if patients requiring specialised care are more expensive to treat than others allocated to the same HRG. To assess this we estimate the additional costs associated with receipt of specialised care. We analyse costs for 12,154,599 patients treated in 163 English hospitals in fiscal year 2008/09 according to the type of specialised care received, if any. We account for the distributional features of patient cost data, and estimate ordinary least squares and generalised linear regression models with random effects to isolate what influence the hospital itself has on costs. We find that, for nineteen types of specialised care, patients do not have higher costs than others allocated to the same HRG. However, costs are higher if a patient has cancer, spinal, neurosciences, cystic fibrosis, children's, rheumatology, colorectal or orthopaedic specialised services. Hospitals might be paid a surcharge for providing these forms of specialised care. We also find substantial variation in the average cost of treatment across the hospital sector, due neither to the provision of specialised care nor to other characteristics of each hospital's patients.

© 2013 Elsevier Ltd. Open access under [CC BY-NC-ND license](http://creativecommons.org/licenses/by-nc-nd/3.0/).

### Introduction

The past few years have seen two forms of specialisation being promoted in the English health system. The first takes the form of what Skinner termed “focused factories”, whereby organizations concentrate on a limited range of activity (Skinner, 1974). Examples in the United States include Ambulatory Care Centres and specialist orthopaedic, cardiac or general surgery hospitals (Barro, Huckman, & Kessler, 2006; Schneider et al., 2008) and, in England, treatment centres dedicated to the delivery of specific treatment such as hip and knee replacement or cataract removal (Department of Health, 2002). There are two main attractions of such focused operations. First, by concentrating on specific procedures, such organizations may be able to attract sufficient volumes of patients to benefit from economies of scale (Schneider et al., 2008; Zwanziger, Melnick, & Simonson, 1996). Second, these organizations may be better able to guarantee that treatment will take place as planned simply because resources are dedicated to the purpose. They, therefore,

avoid competition for resources witnessed in general hospitals (Harris, 1977) where, in the face of capacity constraints, patients admitted as emergencies might be prioritised ahead of others (The Royal College of Surgeons of England, 2007).

But this organizational set-up has its detractors, the main argument being that they focus on less complex patients (Barro et al., 2006; Street, Sivey, Mason, Miraldo, & Siciliani, 2010). There may be sound clinical grounds for this, if dedicated units lack the back-up facilities required should problems arise. But critics argue that these organizations are “cream skimming” for financial reasons, noting that most US specialist hospitals are for-profit and physician owned. Although the number of specialist hospitals in the United States grew from 29 in 1990 to 91 in 2005 the US government imposed a moratorium on further development, concerned primarily that such hospitals were specializing merely on the most profitable procedures (Schneider et al., 2008; Shactman, 2005).

Rather than “cream skimming”, the second strand of English specialisation policy has created the potential for “adverse selection” of more complex patients at specialist centres. This policy involves establishing specialist multidisciplinary teams to care for patients suffering rare conditions, the idea being that the specialist team sees sufficient numbers of such patients to be able to maintain expertise and to deliver best outcomes (Smith, 2002). This

\* Corresponding author. Present address: FAO of the UN, Viale Aventino 1, Rome 00153, Italy. Tel.: +39 0657054857.

E-mail addresses: [silvio.daidone@york.ac.uk](mailto:silvio.daidone@york.ac.uk), [silvio.daidone@gmail.com](mailto:silvio.daidone@gmail.com) (S. Daidone), [andrew.street@york.ac.uk](mailto:andrew.street@york.ac.uk) (A. Street).

<sup>1</sup> Tel.: +44 (0)1904321445; fax: +44 (0)1904 321454.

underpins the primary motivation of the English legal definition of “specialised care” being a service that requires a planning population of more than one million people (NHS Specialised Services, 2010c). Specialised care may also be required if the condition is particularly severe, if the patient suffers other serious underlying problems, or to correct complications following a procedure.

The definition implies that a specialised service should be provided only by those hospitals with the necessary teams and infrastructure. This requirement is not directly regulated by the English Department of Health (DoH), with all NHS hospitals allowed to provide any type of service. Instead the DoH defines those hospitals with the requisite teams as eligible for additional funding related to the provision of specialised care (Department of Health, 2006). After establishing eligibility, the issue arises as to how to pay for specialised care.

As in many countries, English hospitals are funded under a prospective payment system that links a hospital's income to the number and casemix of patients treated (Busse, Geissler, Quentin, & Wiley, 2011). Payments are defined in terms of the healthcare resource group (HRG – the English version of diagnosis related groups) to which each patient is allocated. Allocation is based on which (if any) procedures are received, primary diagnosis, age and level of complications (Mason, Ward, & Street, 2011). The current version, known as HRG4, contains some 1400 groups which are intended to be clinically similar and resource homogeneous. But inevitably each HRG combines patients with below and above average costs. This will not create a funding problem as long as within-HRG variation in costs is random across hospitals. But variation may be systematic if it is related to characteristics of patients that have not been taken explicitly into account in constructing HRGs. One such characteristic is whether or not patients need specialised care. This may make them more expensive to treat than otherwise similar patients allocated to the same HRG. Moreover, by virtue of their care requirements, such patients will be concentrated in those hospitals with the requisite specialist team. The danger is that these hospitals will be underfunded if HRGs fail to account accurately for the differential care requirements of such patients.

There are two options to deal with the problem. The first would be to subdivide HRGs according to whether or not specialised care is provided, in much the same way that groups are divided into severity levels, as in France (Or & Bellanger, 2011), or according to the presence of complications and comorbidities (Kobel, Thuilliez, Bellanger, & Pfeiffer, 2011). A slight drawback of this approach is that because patients receiving specialised care are potentially distributed across all HRGs the number of categories might double, undermining the desirable feature of a limited number of categories (Fetter, Shin, & Freeman, 1980; Kobel et al., 2011). More pertinently, this option also presumes that patients requiring specialised care are indeed more costly to care for than other patients allocated to the same HRG, a presumption that must be established empirically.

The second option would be to make an additional surcharge over and above the prospective price if there is evidence that the receipt of specialised care does increase costs relative to other patients in the same payment category. Countries including Australia, France, Germany, Italy and the US have adopted this type of approach to deal with complexity or specialisation (Ettelt, Thomson, Nolte, & Mays, 2006; Rosko & Carpenter, 1994; Scheller-Kreinsen, Quentin, & Busse, 2011).

In what follows we evaluate whether patients that receive specialised care are more costly to care for than others in the same HRG. The evaluation involves first identifying whether or not a patient received specialised care and, if so, what of type specialised care this was. Specialised care is identified using the English Specialised Services National Definition Sets (SSNDS), which have been

arrived at by clinicians, managers, coding staff, commissioners and patient representatives to support the commissioning of specialised services for patients with rare or complex conditions (NHS Specialised Services, 2010c). The definitions are based on diagnosis or procedure codes which, if present in the patient's medical record, indicate that the patient received specialised care. Having identified which patients received specialised care, we then compare treatment costs for patients allocated to the same HRG who did and did not receive specialised care. Observed costs may be partly attributable to inefficient resource use on the part of the hospital itself so in the comparisons we allow for these possible hospital effects. Finally we assess hospitals in terms of their average costs, having controlled for their patient casemix, and assess whether these costs are related to the proportion of specialised activity undertaken.

In the next section we outline our empirical strategy to investigate the extent to which variations in observed treatment costs are explained, firstly, by whether or not a patient received a specialised service and, secondly, by the hospital in which care is provided. Then we provide a presentation of the data and some descriptive statistics, followed by results. We draw conclusions in the final section.

### Empirical model

Our empirical approach builds on the literature that examines hospital costs using patient-level data, a primary purpose being to identify the relative costs of each hospital (Bradford, Kleit, Krousel-Wood, & Re, 2001; Dormont & Milcent, 2004, 2005; Kessler & McClellan, 2002; Laudicella, Olsen, & Street, 2010; McClellan, 1997; Olsen & Street, 2008). All of these analyses focus on a particular subset of hospital patients. Instead we consider the whole population of patients admitted to English hospitals. There are two advantages to this. First, we are able to derive an estimate of relative cost performance for each hospital as a whole, rather than merely a subset of its activity. Second, because we consider all costs and all activities this estimate is less likely to be contaminated by decisions about how shared costs are allocated across subsets of activity. We first explain how costs are calculated before setting out our empirical model.

#### *Constructing patient costs*

All English hospitals are required to report their activity and costs annually to the DoH applying a standard top-down costing methodology to produce costs for patients allocated to each HRG in each of their departments (Department of Health, 2008b). The NHS Costing Manual sets out rules to ensure that costs are matched as closely as possible to the services that generate them and that maximise direct attribution of costs in preference to apportionment. Costs are calculated on a full absorption basis, meaning that they should reflect the full cost of the service delivered and have to reconcile back to the general ledger. Instructions are provided about which costs should be directly attributable, either to individual patients or departments (e.g. drugs, dressings, surgical implants, clinical and nursing staff); indirect costs shared across patients in different departments or wards, which can usually be attributed on an activity basis (e.g. laundry, maintenance staff); and general overheads which are not related to activity levels in any given year (e.g. rent and rates, senior management). According to these instructions, total hospital costs are progressively cascaded down to treatment and support services (theatres, pharmacy, radiology, pathology, etc), to departments (general surgery, general medicine, obstetrics, etc), to wards, and then to patients according to the HRG in which they are categorised.

These HRG costs form the basis of the Reference Cost return that each hospital reports annually to the DoH (Department of Health, 2012). For patients allocated to the same HRG, hospitals report costs according to whether the patient was admitted as an emergency (non-elective) or following referral, usually from their general practitioner (elective). Further, for elective patients in the same HRG, hospitals separately report costs for those treated on a day case basis and those treated as inpatients. Per diem costs are also reported for patients that stay in hospital beyond HRG specific length of stay trimpoints.

We map these costs to each patient according to the hospital and department in which they were treated, the HRG to which they were allocated, their admission type, and their length of stay, by applying the process described in the first Appendix of the supplementary material. This process generates costs that are the most specific to an individual patient that can be achieved given the top-down cost allocation methods that are used by English hospitals.

In our analyses, all costs reported by hospitals are adjusted by the market forces factor (MFF), this being an index of geographical variation in the prices of land, buildings, and labour (Department of Health, 2008a), designed to account for unavoidable differences in factor prices incurred by different hospitals.

Clear differences in costs exist between patients who do and do not receive specialised care, amounting on average to £1884 and £1385 respectively. Other than the receipt of specialised care, the most obvious reasons that patients have different costs are that they have different care requirements and that they are treated in different hospitals. Our analysis is designed to isolate these influences.

#### Model specifications

The main reason that patients have different costs is that they have different care requirements and, consequently, receive very diverse types of treatment, as is recognised in the HRG-based payment system. However, it is infeasible to introduce dummy variables for all HRGs as there are too many – the English system comprises 1400 groups (Mason et al., 2011). We therefore standardise each patient's cost by the mean cost of all patients allocated to the same HRG. Thus our dependent variable is defined as the patient's cost relative to the average cost of patients in the same HRG:  $\tilde{C}_{ik} = C_{ihk}/\bar{C}_h$  where  $C_{ihk}$  is the cost of patient  $i$  in HRG  $h$  in hospital  $k$  and  $\bar{C}_h$  is the national average cost of all patients allocated to HRG  $h$ .

We take account of the clustering of patients within hospitals by estimating a random effects model. Our preference for the RE rather than fixed effects (FE) specification has been driven by some practical issues. Firstly, the Hausman test rejected the null hypothesis of no systematic difference between FE and RE. Secondly, hospital effects are predicted differently after estimation and this divergence may bring about conflicting policy interpretations. In the RE framework, hospital effects are retrieved from the underlying distribution of the random variable, combining prior information about the parameter values with the information available from the data to obtain posterior means (Skrondal & Rabe-Hesketh, 2009). When the number of patients within a hospital is relatively small, the posterior mean corresponds to the mean of the prior, an attractive property known as "shrinkage towards the mean". Finally, the RE specification can be easily applied to Generalised Linear Models (GLM) (McCullagh & Nelder, 1989). The resulting framework is known as Generalised Linear Mixed Models (GLMM) (McCulloch, 2003), for which the FE approach does not lead to an equivalent straightforward generalisation.

We regress the standardised cost against a set of specialised care markers ( $S$ ), these corresponding to the type of specialised care as

defined in the Specialised Services National Definition Sets. These markers enter as dummy variables, taking the value of 1 if the patient is recorded as having any of the diagnoses or procedures listed in the relevant definition set. The model is specified as:

$$\tilde{C}_{ik} = \alpha + \sum_{n=1}^N \beta_n S_{nik} + u_k + v_{ik} \quad (1)$$

The model includes a random hospital effect  $u_k$  and a random error term,  $v_{ik}$ , for the  $i$ th patient using the  $n$ th specialised service  $S$ , within the  $k$ th hospital (assumed to have zero mean and constant variance  $\sigma_v$ ). The  $\beta$ 's are the parameters of interest: if positive and significant, a patient with the specialist care marker has higher costs than do other patients allocated to the same HRG. In order to get a more easily interpretable measure like the percentage increase,  $g$ , we need to compute the marginal mean for both specialised and unspecialised services, so that

$$g_n = \frac{E(\tilde{C}_i | S_n = 1, S) - E(\tilde{C}_i | S_n = 0, S)}{E(\tilde{C}_i | S_n = 0, S)} * 100 \quad (2)$$

In a linear OLS the coefficients on specialised markers, the  $\beta$ 's, represent the difference in standardised costs between specialised and unspecialised services. Therefore Equation (2) boils down to

$$\frac{\beta_n}{E(\tilde{C}_i | S_n = 0, S)} * 100$$

The  $u_k$  in Equation (1) is the random effect. This captures the effect of the hospital on the cost of any particular patient treated in the hospital over and above the average cost of the HRG and the other explanatory variables included in the model (here, whether and what type of specialised care the patient received). The random effects, then, can be thought as the relative hospital performance in controlling costs. However, this interpretation is conditional upon having properly accounted for other factors that might explain variation in patient costs.

Equation (1) includes only the specialised care markers to explain why the costs of any individual patient might differ from the costs of other patients allocated to the same HRG. But within each HRG, some hospitals might attract more complex patients with more diagnostic problems. If there were systematic differences across hospitals in the type of patients treated within each particular HRG, the estimated random effects would provide an imperfect measure of relative hospital performance. If this is not taken into account the hospital will appear to have higher costs than it should have given the (inaccurately measured) profile of the patients that it treats.

The solution is to assess the extent to which patient characteristics, over and above whether they have received specialised services, explain costs. To this end, we include a set ( $m = 1 \dots M$ ) of additional risk-adjustment variables ( $X$ ) describing each patient. We specify these variables in the next section. The risk-adjusted model takes the form:

$$\tilde{C}_{ik} = \alpha + \sum_{n=1}^N \beta_n S_{nik} + \sum_{m=1}^M \gamma_m X_{mi} + u_k + v_{ik} \quad (3)$$

The random effect in this equation captures the hospital's influence on costs over and above the influence of all the other patient-level variables accounted for in the model. Consequently the cost of a typical patient in a hospital with a relatively large random effect is higher than the cost of a comparable patient treated in a hospital with a lower random effect.

In estimating models (1) and (3), it is important to recognise that hospital cost data are highly skewed with a long right-hand tail (Basu & Rathouz, 2005; Beeuwkes Buntin & Zaslavsky, 2004; Manning & Mullahy, 2001). Usual OLS methods may yield biased and/or less precise estimates of means and marginal effects, since results may not be robust to tail problems. Therefore in selecting our estimation model we compare OLS with: i) OLS for log or square root transformed costs; ii) GLM; and iii) Finite Mixture Models (FMM).

**Data issues and descriptive statistics**

We analyse the hospital episode statistics (HES) for patients discharged from each English NHS acute hospital during the financial year 2008/9. HES comprise individual patient records defined as a Finished Consultant Episode (episode) about every NHS patient admitted to hospital in England. Episodes measure the time patients spend under the care of a particular consultant. We link the episodes for each patient in order to capture information about the full course of hospital treatment (Castelli, Laudicella, & Street, 2008). Our analytical sample consists of 12,154,599 patients treated in 163 hospitals. The selection of the sample is described in detail in the supporting material.

We look at the information in each patient’s medical record to ascertain whether or not specialised care was received, as defined by the Specialised Services National Definition Sets (SSNDS) (NHS Specialised Services, 2010c). The third edition contains 34 definition sets each of which identifies a set of diagnoses and procedures that are deemed either definitively or potentially specialised using the International Classification of Diseases (ICD), version 10, and the OPCS Classification of Interventions and Procedures, version 4.5. We construct a dummy variable for each definition set, taking a value of 1 if any one of the definitive specialised codes appears in the patient’s medical record. For seven definition sets, no definitive codes are provided because additional criteria must be considered in determining whether specialised care is required (for example see NHS Specialised Services (2010a)), so these definition sets are excluded from the analysis. Thus, we construct 27 dummy variables indicating which type of specialised care has been received. We add an additional condition that patients were treated at a hospital deemed by the Department of Health to have the necessary team and infrastructure to provide specialised care and, therefore, to be deemed eligible for specialised funding. We perform a sensitivity analysis that relaxes this latter condition.

In 2008/9, for approximately 1.5 m patients it was indicated that some kind of specialised service was delivered as part of the treatment package. Table 1 reports the number of patients who received each type of specialised services, showing, for instance, that more than 360,000 patients received specialised renal services as defined in the renal SSNDS (NHS Specialised Services, 2010b). Some 32,000 patients received more than one of the broad types of specialised service.

Consider the distribution of specialised services among hospitals. Fig. 1 shows the proportion of each hospital’s patients that received specialised services (the bar height) and the proportions that were eligible (dark) or not (white) for additional payment. As would be expected, most specialised care is provided by those hospitals classified by the Department of Health as eligible providers. Nonetheless, a non-trivial portion of specialised services is provided by hospitals that are not deemed eligible for additional funding for these particular services.

Patient characteristics are derived from information contained in their medical record. In Table 2 we report descriptive statistics of the explanatory variables used in the right-hand side of Equation (3). Patients receiving specialised services are more likely to be

**Table 1**  
Number of patients identified as receiving specialised care, defined for each Specialised Services National Definition Set (SSNDS).

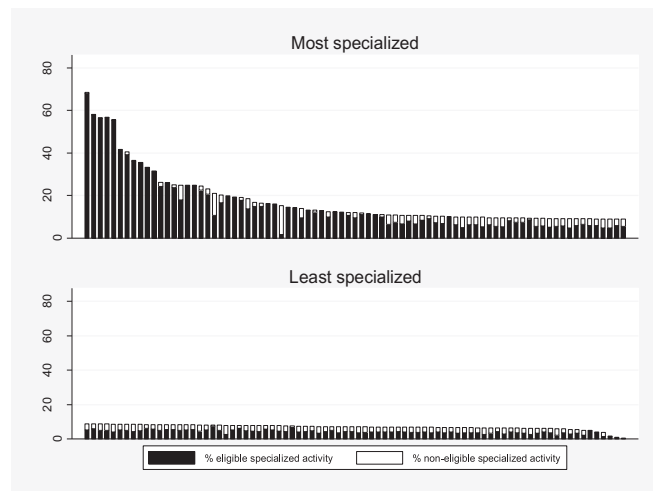
SSNDS	#	SSNDS	#
No spec. serv.	10,901,844	Dermatology	10,790
Cancer	14,035	Rheumatology	358
Blood & marrow transplantation	1050	Endocrinology	7028
Haemophilia	146	Respiratory	71,824
Women	22,551	Vascular diseases	801
Spinal	2167	Pain management	753
Neurosciences	23,848	Ear surgery	1704
Cystic fibrosis	91,868	Colorectal	6838
Renal	360,957	Orthopaedic	3671
Intestinal failure	2380	Morbid obesity	7905
Cardiology & cardiac surgery	89,127	Metabolic disorders	3182
Cleft lip & palate	222,939	Ophthalmology	6345
Infectious diseases	2203	Haemoglobinopathy	146,403
Liver, biliary & pancreatic	14,807	>1 spec. serv.	32,311
Children	104,764	Total	12,154,599

male and younger (probably mainly because infants are more likely to require specialised activity, 16% of them at birth), to have been cared for by more than one consultant during their hospital stay, and to have been transferred between hospitals. As the diagnostic characteristics were constructed using ICD10 codes, there might be some overlap with the codes used for the definition of specialised services. However, other than a very small correlation between obesity and morbid obesity services, we found no correlation between the specialised services and other patient characteristics.

**Results**

*Distribution of patient costs*

In order to compare the large variety of models to analyse patient costs, we undertake a quasi-experimental approach following an approach developed by Deb and Burgess (Deb & Burgess, 2008). We randomly split observations into two groups; half are assigned to the estimation group and the remaining half to the prediction group. We extract random samples with replacement of size  $N = \{20,000\ 50,000\ 200,000\ 500,000\ 1,000,000\}$  from the estimation group. Then we estimate Equation (3) and save parameter results for eight models. We repeat this procedure thirty times. Finally we calculate conditional means using all the observations from the prediction group.



**Fig. 1.** Distribution of specialised activity among providers.

**Table 2**  
Descriptive statistics of explanatory variables (st. dev. in parenthesis).

Variable	Description	Not spec	Spec	Tot	Variable	Description	Not spec	Spec	Tot
female1	=1, Patient is female	57.4 (49.5)	44.5 (49.7)	56.0 (49.6)	riskfact	=1, Patient with other lifestyle risk factors	0.729 (8.51)	0.265 (5.14)	0.681 (8.22)
age	Patient age at the beginning of the spell	51.61 (24.24)	49.94 (25.70)	51.44 (24.40)	congmalf	=1, Patient with congenital malformations	1.13 (10.6)	4.87 (21.5)	1.51 (12.2)
urban1	=1, Urban area	0.818 (38.6)	0.817 (38.7)	0.818 (38.6)	risk_phys	=1, Patient exposed to physical risk factors	0.064 (2.54)	0.119 (3.45)	0.07 (2.65)
white1	=1, ethnicity is white	79.4 (40.4)	78.9 (40.8)	79.4 (40.4)	risk_psysoc	=1, Patient with problems related to psychosocial circumstances	0.384 (6.19)	0.157 (3.95)	0.361 (6.00)
episodes	Number of episodes in the spell	1.118 (0.426)	1.108 (0.545)	1.117 (0.440)	East of England	=1, Region of treatment: East of England	8.98 (28.6)	8.23 (27.5)	8.91 (28.5)
emerg	=1, Patient admitted as emergency	38.3 (48.6)	15.9 (36.6)	36 (48.0)	London	=1, Region of treatment: London	14.4 (35.1)	14.7 (35.4)	14.4 (35.1)
die	=1, Patient died	1.55 (12.4)	1.81 (13.3)	1.58 (12.5)	North-East	=1, Region of treatment: North-East	6.40 (24.5)	4.70 (21.2)	6.23 (24.2)
tr_in_el	=1, Patient transferred from an eligible provider	0.004 (0.628)	0.0164 (1.28)	0.005 (0.723)	North-West	=1, Region of treatment: North-West	16.4 (37.0)	13.8 (34.5)	16.1 (36.8)
tr_in_nonel	=1, Patient transferred from a non-eligible provider	2.65 (16.1)	4.14 (19.9)	2.8 (16.5)	South-East	=1, Region of treatment: South-East	12.7 (33.3)	13.2 (33.8)	12.7 (33.3)
tr_out_el	=1, Patient transferred to an eligible provider	0.501 (7.06)	0.491 (6.99)	0.5 (7.05)	South-West	=1, Region of treatment: South-West	11.2 (31.5)	12.6 (33.2)	11.3 (31.7)
tr_out_nonel	=1, Patient transferred to a non-eligible provider	1.13 (10.6)	1.35 (11.5)	1.16 (10.7)	West Midlands	=1, Region of treatment: West Midlands	11.2 (31.5)	12.4 (32.9)	11.3 (31.7)
pregnancy	=1, One of the patient diagnosis is: pregnancy or childbirth	10.4 (30.6)	0.528 (7.25)	9.41 (29.2)	Yorkshire	=1, Region of treatment: Yorkshire	11.2 (31.6)	14.7 (35.4)	11.6 (32.0)
drug	=1, Patient is drug user or drug dependent	0.324 (5.68)	0.203 (4.50)	0.312 (5.57)	imd04c	Index of multiple deprivation: crime	0.0526 (0.839)	0.0613 (0.852)	0.0535 (0.841)
alcohol	=1, Patient is alcohol user or alcohol dependent	1.7 (12.9)	0.732 (8.52)	1.6 (12.5)	imd04ed	Index of multiple deprivation: education, skills and training	23.75 (19.82)	24.91 (20.63)	23.87 (19.91)
smoke	=1, Patient is tobacco user or tobacco dependent	3.69 (18.9)	3.48 (8.30)	3.67 (18.8)	imd04hd	Index of multiple deprivation: health deprivation and disability	0.129 (0.904)	0.151 (0.911)	0.131 (0.905)
obesity	=1, Patient with obesity problems	0.72 (8.45)	1.4 (11.8)	0.791 (8.86)	imd04hs	Index of multiple deprivation: barriers to housing and services	21.26 (10.95)	21.31 (10.73)	21.26 (10.93)
allergy	=1, Patient with personal history of allergy	2.76 (16.4)	1.91 (13.7)	2.67 (16.1)	imd04i	Index of multiple deprivation: income deprivation	0.170 (0.128)	0.174 (0.130)	0.171 (0.128)
diabetes	=1, Patient with diabetes problems	7.85 (26.9)	6.26 (24.2)	7.69 (26.6)	imd04ia	Index of multiple deprivation: income deprivation affecting older people	0.214 (0.132)	0.218 (0.135)	0.214 (0.132)

Table 2 (continued)

Variable	Description	Not spec	Spec	Tot	Variable	Description	Not spec	Spec	Tot
hypertens	=1, Patient with hypertension problems	17.1 (37.6)	12.1 (32.6)	16.5 (37.2)	imd04ic	Index of multiple deprivation: income deprivation affecting children	0.227 (0.180)	0.232 (0.183)	0.227 (0.180)
haemorr	=1, Patient with haemorrhage/coagulation problems	0.393 (6.26)	0.899 (9.44)	0.445 (6.66)	imd04le	Index of multiple deprivation: living environment	22.56 (17.30)	22.36 (17.15)	22.54 (17.29)
histdis	=1, Patient with personal history of diseases	10.8 (31.0)	8.66 (28.1)	10.6 (30.7)	imd04rk	Index of multiple deprivation: overall ranking	15100.4 (9386.3)	14882.9 (9492.0)	15077.9 (9397.5)

Notes: age expressed in years, number of episodes in units, imd variables have index-specific domains, all other variables are expressed as percentages.

In order to assess the quality of the predictions we use two statistics that are common in this kind of analysis: a) the mean prediction error (MPE) and b) the mean absolute prediction error (MAPE), which measure predictive accuracy on average and for individual observations. Results confirm that, compared to the other models, simple OLS has very good predictive performance both on average and for individuals (Table 3). Accuracy improves as the sample increases, but not monotonically. Log-linear OLS models are the least precise, even allowing for Duan correction factors (Duan, Manning, Morris, & Newhouse, 1983). The FMM with two components suffered convergence problems, particularly for the sample of 20,000 observations. Therefore in Table 3 the average MPE and MAPE is given by the models that achieved convergence. In terms of performance, FMM is positioned behind linear OLS and GLM, but is more accurate than log-linear models. Given these results, we decided to undertake the analysis on the full data with just a linear OLS model and a GLM with a gamma distribution and square root link. Gamma distributions were chosen based on the results of modified Park tests.

#### Specialist mark-ups

In Table 4 we report the predicted percentage increase in costs for specialised services for the two equations using OLS and GLM. The specialised markers where estimates are statistically significant ( $p$ -value < 0.01) appear in bold. There are some general issues to note.

First, the significance of the specialist markers is consistent across specifications. This means that we can be confident in interpreting (i) a significant positive coefficient as indicating that the specialist marker has a significant positive impact on cost and (ii) a non-significant coefficient as indicating no significant impact of this type of specialised care on costs.

Second, for the same specification (Equation (1) or (3)) the OLS and GLM estimates are very similar, differing by no more than 1.25 percentage points for all but one specialist marker, infectious disease, for which GLM estimates are 3 percentage points lower. The general consistency of results is unsurprising given the large sample sizes.

Third, for five types of specialised care, estimates of the additional costs differ by more than one percentage point when comparing Equation (1) and the risk-adjusted Equation (3). This is evident for specialised care for neurosciences, cystic fibrosis, children, rheumatology and vascular diseases (for which the significance level also falls from  $p < 0.01$  to  $p < 0.05$ ). This implies that the set of patient characteristics used as risk-adjustment variables are jointly correlated with the type of specialised care in question. For those hospitals that provide these types of care, it will be particularly important to account for these characteristics when making judgements about relative hospital performance based on the random effects.

The specialised services that drive higher costs relative to other patients allocated to the same HRG are cancer (18% higher costs),

Table 3  
Average performance of competing models.

Model	Statistics	Estimation sample				
		20,000	50,000	200,000	500,000	1,000,000
1	MPE	-0.006659	<b>-0.004329</b>	-0.003627	<b>-0.002550</b>	<b>-0.002534</b>
	MAPE	0.471862	0.469603	0.468406	<b>0.467833</b>	<b>0.467753</b>
2	MPE	-2.411588	-1.626989	-0.874667	-0.877367	-0.840543
	MAPE	2.870144	2.088513	1.337236	1.340781	1.303992
3	MPE	-2.708189	-1.832423	-0.989557	-0.994005	-0.952426
	MAPE	2.881833	2.006294	1.162441	1.167355	1.125775
4	MPE	-2.138670	-2.063748	-2.010085	-1.902191	-1.948482
	MAPE	2.243711	2.166274	2.108399	2.002521	2.046431
5	MPE	-0.008342	-0.005645	-0.004713	-0.003663	-0.003672
	MAPE	0.473157	0.470833	0.469535	0.469020	0.468967
6	MPE	-0.006665	-0.004370	-0.003781	-0.002726	-0.002728
	MAPE	<b>0.471149</b>	<b>0.469311</b>	<b>0.468381</b>	0.467870	0.467810
7	MPE	<b>-0.065603</b>	-0.004975	<b>-0.003580</b>	-0.003253	-0.002179
	MAPE	0.532327	0.471940	0.470543	0.471467	0.470718
8	MPE	-0.400378	-0.336326	-0.334915	-0.322274	-0.325995
	MAPE	0.770003	0.707454	0.685659	0.679344	0.680713

Notes: MPE – mean prediction error; MAPE – mean average prediction error. Models: 1) OLS, 2) OLS on logged costs without Duan correction, 3) OLS on logged costs with Duan correction, 4) OLS on square root costs, 5) GLM with gamma distribution and log link, 6) GLM with gamma distribution and square root link, 7) GLM with gamma distribution and power –1 link, 8) FMM with 2 components.

Averages for 30 replications, except for model 8 which includes only statistics for replications where convergence has been achieved. Numbers in bold indicate the best model in terms of one of the two statistics.

**Table 4**  
Estimates of additional costs associated with receipt of specialised care (%).

Equation:	OLS – linear		GLM – gamma family, square root link	
	[1]	[3]	[1]	[3]
Cancer	<b>0.1842</b>	<b>0.1879</b>	<b>0.1852</b>	<b>0.1838</b>
BMT	–0.1045	–0.0897	–0.0858	–0.0555
Haemophilia	–0.1435	–0.2022	–0.1418	–0.1735
Womens	–0.0192	–0.0157	–0.0180	–0.0092
Spinal	<b>0.2755</b>	<b>0.2729</b>	<b>0.2785</b>	<b>0.2775</b>
Neurosciences	<b>0.2286</b>	<b>0.1691</b>	<b>0.2246</b>	<b>0.1807</b>
Cystic fibrosis	<b>0.3792</b>	<b>0.3347</b>	<b>0.3798</b>	<b>0.3282</b>
Renal	–0.1117	–0.0868	–0.1121	–0.0849
Intestinal failure	0.0017	–0.0196	0.0044	–0.0169
Cardiology	0.0007	–0.0600	0.0002	–0.0386
Cleft lip	–0.0423	–0.0144	–0.0435	–0.0069
Infectious diseases	<b>0.2129</b>	<b>0.2049</b>	<b>0.1885</b>	<b>0.1700</b>
Liver	0.0754	0.0637	0.0760	0.0631
Children	<b>0.1997</b>	<b>0.1742</b>	<b>0.1929</b>	<b>0.1644</b>
Dermatology	–0.0087	–0.0037	–0.0092	0.0000
Rheumatology	<b>0.1298</b>	<b>0.1618</b>	<b>0.1295</b>	<b>0.1754</b>
Endocrinology	–0.0071	0.0110	–0.0104	0.0089
Respiratory	–0.0381	–0.0743	–0.0409	–0.0732
Vascular diseases	<b>0.2112</b>	<u>0.1753</u>	<b>0.2032</b>	0.1629
Pain management	0.1902	0.2200	0.1687	0.2253
Ear surgery	–0.0006	0.0183	–0.0007	0.0250
Colorectal	<b>0.2105</b>	<b>0.2150</b>	<b>0.2137</b>	<b>0.2198</b>
Orthopaedic	<b>0.2130</b>	<b>0.2248</b>	<b>0.2073</b>	<b>0.2180</b>
Morbid obesity	–0.0075	–0.0106	–0.0068	–0.0052
Metabolic disorders	–0.0155	0.0023	–0.0205	–0.0198
Ophthalmology	0.0570	0.0784	0.0546	0.0802
Haemoglobinopathy	0.0031	0.0131	0.0000	–0.0056
Obs.	12,154,599	12,154,599	12,154,599	12,154,599
R <sup>2</sup> /Log-pseudolikelihood	0.0020	0.0080	–10,317,120	–9,971,890

Notes: Bold figures 1% significant, underlined figures 5% significant. Clustered SE by hospital ID.

spinal (28%), neurosciences (23%), cystic fibrosis (38%), children's (20%), rheumatology (13%), colorectal (21%) and orthopaedic (21%). Compared to otherwise similar patients, those that receive specialised services tend also to have longer lengths of stay, which contributes to their higher costs. The considerably higher additional costs for specialised spinal services and cystic fibrosis services are partly a reflection that patients requiring these types of care often also receive other types of specialised care (almost a quarter of cystic fibrosis and a half of spinal patients).

Table 5 reports the coefficients associated with the risk-adjustment variables for both the OLS and GLM versions of Equation (3) (the specialist markers previously reported in Table 4 are not reported). This table shows that, compared to other patients in the same HRG and over and above the influence of specialised care, patients have higher costs ( $p < 0.01$ ) if they are pregnant (pregnancy), suffer allergy (allergy), congenital malformations (congmalf) or problems related to psychosocial circumstances (risk\_psysoc), were transferred between hospitals (tr\_\*) or consultants (episodes) during their treatment, if they died in hospital, of if they were treated in London (despite the MMF correction for the higher costs of labour, land and buildings). Patients diagnosed with alcohol problems have slightly lower (4–5%) costs. The relationship between cost and the deprivation of the patient's area of residence (imd\*) is sensitive to the deprivation indicator and to the choice of OLS and GLM but generally appears insignificant. Age does not have a significant influence on costs, probably because this is already accounted for in the construction of HRGs.

#### Sensitivity analyses

Our estimates are generally robust to alternative definitions of specialised care (table of results shown in the supporting material).

**Table 5**  
Complete model (Equation (3)), estimates of explanatory variables coefficients.

	OLS		GLM		
	OLS	GLM	OLS	GLM	
imd04c	0.000	0.021	tr_out_nonel	<b>0.129</b>	<b>0.129</b>
imd04ed	0.000	0.000	die	<b>0.072</b>	<b>0.073</b>
imd04hd	–0.009	–0.022	emerg	–0.013	–0.023
imd04hs	0.000	0.001	episodes	<b>0.108</b>	<b>0.106</b>
imd04i	<u>0.090</u>	–0.075	East of England	0.115	0.109
imd04ia	–0.047	<u>0.104</u>	London	<b>0.160</b>	<b>0.140</b>
imd04ic	– <b>0.078</b>	–0.014	North-East	0.022	0.033
imd04le	0.000	–0.001	North-West	0.009	–0.017
imd04rk	<b>0.000</b>	0.000	South-East	0.068	0.081
pregnancy	<b>0.079</b>	0.057	South-West	0.007	–0.021
drug	–0.001	–0.009	West Midlands	0.044	0.030
alcohol	– <b>0.041</b>	– <b>0.051</b>	Yorkshire	0.055	<u>0.080</u>
smoke	–0.008	–0.005	urban1	–0.003	0.005
obesity	0.013	0.026	white1	<u>0.015</u>	0.008
allergy	<b>0.026</b>	<u>0.024</u>	female1	0.599	0.431
diabetes	–0.008	–0.018	male1	0.600	0.434
hypertens	0.047	0.056	age	0.085	0.070
haemorr	<u>0.081</u>	<u>0.071</u>	age2	–0.002	<u>–0.002</u>
histdis	0.020	0.020	age3	0.000	<u>0.000</u>
riskfact	0.001	–0.012	femage	–0.086	–0.071
congmalf	<b>0.051</b>	<b>0.058</b>	femage2	0.002	<u>0.002</u>
risk_phys	–0.007	0.004	femage3	0.000	<u>0.000</u>
risk_psysoc	<b>0.192</b>	<b>0.175</b>	malage	–0.087	<u>–0.071</u>
tr_in_el	0.008	0.012	malage2	0.002	<u>0.002</u>
tr_in_nonel	<u>0.160</u>	<b>0.157</b>	malage3	0.000	<u>0.000</u>
tr_out_el	<b>0.140</b>	<b>0.122</b>	_cons	0.260	– <b>0.630</b>

Notes: Bold figures 1% significant, underlined figures 5% significant. Clustered SE by hospital ID. Reference category for gender is patients with unknown sex or undergoing sex change.

In particular, in sensitivity analyses we relax the condition that patients have to be treated in eligible hospitals and we exclude patients from the analysis if they were allocated to HRGs in which either fewer than 10 patients did not receive specialised care or fewer than 10 patients did receive specialised care.

In the first case, the estimated marginal effect in both equations is unchanged, except for spinal and children's services, for which we observe a reduction of ten percentage points. The difference arises because patients receiving specialised spinal and children's services are not concentrated exclusively among those hospitals deemed eligible by the Department of Health for additional payments. The lower estimates for these types of specialised care imply that hospitals that specialise in providing these services and are eligible for additional funding are more expensive than those that do not specialise, all else equal.

The results are not sensitive to excluding patients in particular HRGs, except for vascular diseases services, for which the marginal cost becomes 7 percentage points higher, and blood and marrow transplantation services, where the marker becomes positive and significant. The sensitivity of results for these two specialised services is due to considerably fewer patients now being identified as receiving specialised care for these services. Therefore, this implies that the HRGs for these services are already capturing the specialised nature of care for the majority of patients receiving vascular and blood and marrow transplantation services.

#### Hospital performance

As would be expected, the vast majority of the variance in patient costs is due to whether they receive specialised care and to their different characteristics rather than to the hospital in which they are treated. This is evidenced by  $\rho = \sigma_u^2 / (\sigma_u^2 + \sigma_\epsilon^2) = 0.017$  for the OLS Equation (3).

Nevertheless, there are differences among hospitals in the size of their random effects, implying variation in average costs across

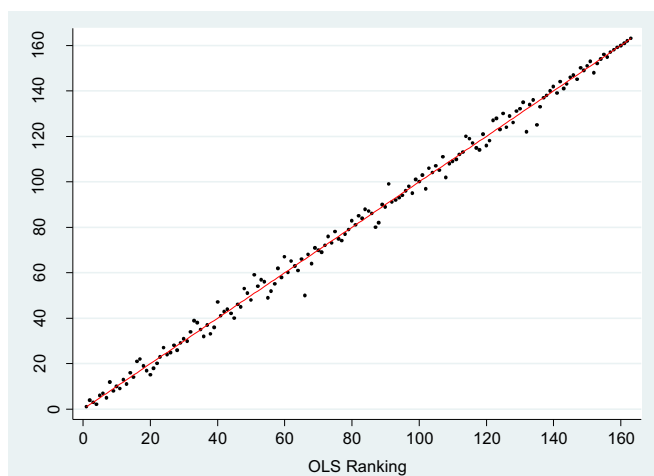


Fig. 2. Ranking of random effects: OLS vs. GLM model.

hospitals in treating otherwise similar patients. Hospitals can be ranked according to their random effect, ordered from those with the lowest average costs for their patients to those with the highest average costs. Ranking is not sensitive to linear OLS and GLM forms of the model, the correlation between the random effects for the two versions of Equation (3) amounting to  $\rho = 0.99$ . For a handful of hospitals there are some movements but for most hospitals the ranking is little changed, as can be seen in Fig. 2. Deviations from the 45° line are completely negligible at the bottom and at the top of the rankings and minor in the middle.

We explored the relationship between each hospital's random effect and the extent to which it provided specialised care, measured as the number of patients receiving specialised care as a proportion of total activity. We found a moderate correlation of around 32–34% depending on the OLS or GLM model. We explored this further by performing regressions for specialised vs. non-specialised providers of children's care. We defined a hospital as a "specialised" provider of children's services either if more than 5% of its care provided to children was specialised or if it defines itself as a specialised Children's hospital. The estimated effect for children services is always lower for these "specialised" providers, probably because they can better exploit economies of scale.

## Conclusions and discussion

We have evaluated the possibility that hospitals providing specialised care might be financially disadvantaged under a prospective payment regime because HRGs do not account fully for the cost implications of specialised services. Our analysis involved calculating the additional costs associated with receipt of specialised care for more than 12 million patients treated in 163 English hospitals during 2008/9. We compared various functional forms in terms of their ability to predict the distribution of our cost data and found that OLS and GLM were superior to logarithmic transformations and finite mixture models. The performance of OLS relative to other models is due to a large sample size which produces unbiased estimates and precise individual predictions. Unsurprisingly, individual predictions are better when a GLM with gamma distribution is used for smaller samples, as this distribution is better able to accommodate the skewed nature of the cost data.

Of course, in any empirical analysis one can question the data, both in terms of its representativeness and accuracy. A major strength of our study is the large sample size, consisting of almost the entire English patient population. Nevertheless some patients

were omitted because of missing data, the main reason being an absence of costs which was non-random across hospitals. Thus results may be biased in an indeterminate direction. It should be recognised, though, that this limitation applies not just to our study but to the English reimbursement regime itself. The payments are supposed to reflect the national average costs for all patients allocated to the same HRG (Street & Maynard, 2007), but if the cost data are absent from our study, they are also absent from the calculation of the tariffs. Ultimately it is for hospitals themselves to improve their costing and reporting processes to ensure that they are not disadvantaged by having their patients under-represented in analyses conducted for purposes of payment design. Evaluation of future years' data may be more comprehensive.

Our study relies on agreed definitions of what constitute specialised care for particular types of patients. In England, there are 34 sets of definitions (SSNDS) each of which has been "approved by the National Specialised Commissioning Group and endorsed by the relevant professional organisations" (NHS Specialised Services, 2010c). For 27 of the SSNDS, definitions are based on diagnosis or procedure codes which, if present in the patient's medical record, are said to provide a definitive indication of the receipt of specialised care. Our analysis takes these definitions as given and investigates the cost consequences of patients with these diagnosis or procedure codes. Of course, one might question the validity of these definitions of specialised care, in particular the use of procedural codes given that the choice of procedure is partially a clinical decision that may vary among clinicians that treat otherwise similar patients. This criticism, however, applies equally to the construction of HRGs themselves, which are somewhat atypical among DRG-type systems in being based on both procedure and diagnosis codes (Kobel et al., 2011).

Our analysis suggests that, for some types of specialised care, costs are indeed higher than for other patients allocated to the same HRG. The implication for payment policy is that hospitals that treat such patients might be paid an additional surcharge over and above the payment associated with the HRG to which these patients are allocated. The size of additional surcharge might be up to the percentage increase in costs as reported for Equation (1) in Table 4. Implementation should be on a budget neutral basis, involving a reallocation from the base national HRG tariffs to pay for any surcharges to be made for specialist care.

The specialised services meriting surcharges are cancer (18% higher payment than for other patients in the same HRG), spinal (28%), neurosciences (23%), cystic fibrosis (38%), children's (20%), rheumatology (13%), colorectal (21%) and orthopaedic (21%). Surcharges would not be made in the presence of the other specialised care markers, there being insufficient evidence to suggest that the costs associated with these types of specialised care drive higher costs.

While we recommend that the amount of payment reflects the estimated percentage increase in costs, different values could be adopted, justified on other grounds. These grounds may include: transitional arrangements, notably for children's services, where the recommended value of 20% is substantially lower than the 78% surcharge that applied when our analysis was commissioned (Department of Health, 2011); materiality, where an additional top-up would have limited financial consequence for those types of specialised services that are delivered to only a small number of patients; and sensitivity to model specification, though these generally prove immaterial.

Our analysis also demonstrates that there is substantial variation in the average cost of treatment across the hospital sector, and that this variation is due neither to the provision of specialised services, and nor to the casemix, diagnostic or socio-demographic characteristics of each hospital's patients. After controlling for



these diverse reasons for cost variation, we are able to rank hospitals according to their relative average costs. Those hospitals rated as relatively costly will struggle financially under a prospective payment system.

## Acknowledgements

We would like to thank Sam Alderson, Rachel Allen, Martin Campbell, Katharina Hauck, Nigel Rice, Eileen Robertson, Andy Sutherland, Matt Sutton and members of the Department of Health's analytical sub-group for Payment by Results. A special thanks also to Mauro Laudicella for his help with the analysis of HES database, and to Fareeda Pathan, Philip Pryor and J. Jill Tao of the SAS Technical Support for their valuable assistance. We also thank the journal's reviewers for their helpful comments. 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.

## Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.socscimed.2013.02.005>.

## References

- Barro, J. R., Huckman, R. S., & Kessler, D. P. (2006). The effects of cardiac specialty hospitals on the cost and quality of medical care. *Journal of Health Economics*, 25(4), 702–721.
- Basu, A., & Rathouz, P. (2005). Estimating marginal and incremental effects on health outcomes using flexible link and variance function models. *Biostatistics*, 6(1), 93–109.
- Beeuwkes Buntin, M., & Zaslavsky, A. (2004). Too much ado about two-part models and transformation? Comparing methods of modelling Medicare expenditures. *Journal of Health Economics*, 23, 525–542.
- Bradford, W. D., Kleit, A. N., Krousel-Wood, M. A., & Re, R. N. (2001). Stochastic frontier estimation of cost models within the hospital. *Review of Economics and Statistics*, 83(2), 302–309.
- Busse, R., Geissler, A., Quentin, W., & Wiley, M. (2011). *Diagnosis-related groups in Europe: Moving towards transparency, efficiency and quality in hospitals*. Maidenhead: Open University Press.
- Castelli, A., Laudicella, M., & Street, A. (2008). *Measuring NHS output growth*. York: Centre for Health Economic, Research paper 43.
- Deb, P., & Burgess, J. F. (2008). *Modelling severely skewed health outcomes: A quasi-experimental model comparison*. Indiana University-Purdue University Indianapolis and Hunter College, City University of New York.
- Department of Health. (2002). *Growing capacity: Independent sector diagnosis and treatment centres*. London: Department of Health.
- Department of Health. (2006). *Review of commissioning arrangements for specialised services (the Carter review)*. London: Department of Health.
- Department of Health. (2008a). *2009–10 and 2010–11 PCT recurrent revenue allocations exposition book*. Leeds: Department of Health.
- Department of Health. (2008b). *NHS costing manual 2007/08*. London: Department of Health.
- Department of Health. (2011). *Payment by results guidance for 2011–12*. Leeds: Department of Health.
- Department of Health. (2012). *Reference costs guidance for 2011–12*. Leeds: Department of Health.
- Dormont, B., & Milcent, C. (2004). The sources of hospital cost variability. *Health Economics*, 13, 927–939.
- Dormont, B., & Milcent, C. (2005). How to regulate heterogeneous hospitals? *Journal of Economics and Management Strategy*, 14(3), 591–621.
- Duan, N., Manning, W. G., Morris, C. M., & Newhouse, J. P. (1983). A comparison of alternative models for the demand of medical care. *Journal of Business and Economic Statistics*, 1, 115–126.
- Ettel, S., Thomson, S., Nolte, E., & Mays, N. (2006). *Reimbursing highly specialised hospital services: The experience of activity-based funding in eight countries*. London: London School of Hygiene and Tropical Medicine.
- Fetter, R. B., Shin, Y., & Freeman, J. L. (1980). Case mix definition by diagnosis-related groups. *Medical Care*, 18(Suppl. 2), 1–53.
- Harris, J. E. (1977). The internal organisation of hospitals: some economic implications. *Bell Journal of Economics*, 467–482.
- Kessler, D., & McClellan, M. (2002). The effects of hospital ownership on medical productivity. *Rand Journal of Economics*, 33(3), 488–506.
- Kobel, C., Thuilliez, J., Bellanger, M. M., & Pfeiffer, K.-P. (2011). DRG systems and similar patient classification systems in Europe. In R. Busse (Ed.), *Diagnosis-related groups in Europe: Moving towards transparency, efficiency and quality in hospitals*. Maidenhead: Open University Press.
- Laudicella, M., Olsen, K. R., & Street, A. (2010). Examining cost variation across hospital departments – a two-stage multilevel approach using patient level data. *Social Science & Medicine*, 71, 1872–1881.
- McClellan, M. (1997). Hospital reimbursement incentives: an empirical analysis. *Journal of Economics and Management Strategy*, 6(1), 91–128.
- McCullagh, P., & Nelder, J. A. (1989). *Generalized linear models*. London: Chapman and Hall.
- McCulloch, C. E. (2003). *Generalized linear mixed models*. Beachwood, Ohio: Institute of Mathematical Statistics.
- Manning, W., & Mullaly, J. (2001). Estimating log models: to transform or not to transform? *Journal of Health Economics*, 20, 461–494.
- Mason, A., Ward, P., & Street, A. (2011). England: the healthcare resource group system. In R. Busse (Ed.), *Diagnosis-related groups in Europe: Moving towards transparency, efficiency and quality in hospitals*. Maidenhead: Open University Press.
- NHS Specialised Services. (2010a). *Specialised burn care services (all ages) – Definition no. 9*. London: Department of Health. [http://www.specialisedservices.nhs.uk/library/26/Specialised\\_Burn\\_Care\\_Services\\_all\\_ages.pdf](http://www.specialisedservices.nhs.uk/library/26/Specialised_Burn_Care_Services_all_ages.pdf).
- NHS Specialised Services. (2010b). *Specialised renal services (adult) – Definition no. 11*. London: Department of Health. [http://www.specialisedservices.nhs.uk/library/26/Specialised\\_Renal\\_Services\\_adult.pdf](http://www.specialisedservices.nhs.uk/library/26/Specialised_Renal_Services_adult.pdf).
- NHS Specialised Services. (2010c). *Specialised services national definition set (3rd ed.)*. London: Department of Health. [http://www.specialisedservices.nhs.uk/documents/index/document\\_category\\_id:26](http://www.specialisedservices.nhs.uk/documents/index/document_category_id:26).
- 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, 671–681.
- Or, Z., & Bellanger, M. M. (2011). France: homogenous patient groups in a heterogeneous hospital market. In R. Busse (Ed.), *Diagnosis-related groups in Europe: Moving towards transparency, efficiency and quality in hospitals*. Maidenhead: Open University Press.
- Rosko, M. D., & Carpenter, C. E. (1994). The impact of intra-DRG severity of illness on hospital profitability: implications for payment reform. *Journal of Health Politics, Policy and Law*, 19(4), 729–751.
- Scheller-Kreinsen, D., Quentin, W., & Busse, R. (2011). DRG-Based hospital payment systems and technological innovation in 12 European countries. *Value in Health*, 14(8), 1166–1172.
- Schneider, J. E., Miller, T. R., Ohsfeldt, R. L., Morrissy, M. A., Zelner, B. A., & Li, P. (2008). The economics of specialty hospitals. *Medical Care Research and Review*, 65(5), 531–553.
- Shactman, D. (2005). Specialty hospitals, ambulatory surgery centers, and general hospitals: charting a wise public policy course. *Health Affairs*, 24(3), 868–873.
- Skinner, W. (May–June 1974). The focused factory. *Harvard Business Review*, 113–120.
- Skrondal, A., & Rabe-Hesketh, S. (2009). Prediction in multilevel generalized linear models. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 172, 659–687.
- Smith, M. (2002). Efficacy of specialist versus non-specialist management of spinal cord injury. *Spinal Cord*, 40, 10–16.
- Street, A., & Maynard, A. (2007). Activity based financing in England: the need for continual refinement of payment by results. *Health Economics, Policy and Law*, 2, 419–427.
- Street, A., Sivey, P., Mason, A., Miraldo, M., & Siciliani, L. (2010). Are English treatment centres treating less complex patients? *Health Policy*, 94, 150–157.
- The Royal College of Surgeons of England. (2007). *Separating emergency and elective surgical care: Recommendations for practice*. London: The Royal College of Surgeons of England.
- Zwanziger, J., Melnick, G. A., & Simonson, L. (1996). Differentiation and specialization in the California hospital industry 1983 to 1988. *Medical Care*, 34(4), 361–372.